REFINED MALATHION AQUATIC EXPOSURE MODELING FOR ENDANGERED SPECIES IN STATIC WATER HABITATS: OHIO RIVER BASIN HUC2 CASE STUDY

FINAL REPORT

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Prepared for:

FMC Corporation
Paul Whatling
1600 Wilson Boulevard, Suite 700
Arlington, VA 22209
Tel. / 703.373.8885
E-Mail / Paul.Whatling@fmc.com

Prepared by:

Stone Environmental, Inc.

535 Stone Cutters Way
Montpelier, VT 05602
Tel. / 802.229.4541
E-Mail / sei@stone-env.com

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[Signature]: Paul Whatling

Paul Whatling
Director, Regulatory Science – US and Canada
FMC Corporation

June 10th, 2016

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Author and Title	Signature	Date
Lauren E. Padilla, Senior Environmental Modeler	Lauren Padilla	6/10/2016
Michael F. Winchell Senior Environmental Modeler	Michael Winchell	6/10/2016

Sponsor/Submitter and Title	Signature	Date
Paul Whatling Senior Registration Manager FMC Corporation	Paul Whatling	6/10/2016

Additional Contributors Include: James Huntington, Barbara Patterson, Naresh Pai, and Sam Beguin from Stone Environmental, Inc.

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EXECUTIVE SUMMARY

The purpose of this study was to provide an improved approach to Step 2 aquatic exposure modeling in the biological evaluation of endangered species. This assessment demonstrates a pilot approach that directly addresses many of the deficiencies in the draft EPA Biological Evaluations for the organophosphates and is provided in response to the EPA's call for recommendations from stakeholders. The improved approach is piloted for endangered aquatic species inhabiting static water habitats in the Ohio River basin, HUC2 05. The assessment evaluated all endangered crustaceans and mollusks, particularly toxicologically sensitive taxa, that may inhabit water bodies corresponding to EPA generalized habitat bins 6 and 7.

The refined Step 2 aquatic exposure modeling approach differed significantly from the Step 2 aquatic exposure modeling approach presented in EPA's malathion BE (EPA, 2016a), and followed many of the NAS panel recommendations on approaches for estimating risks to endangered species from pesticides (NRC, 2013). Improvements to the approach focused on quantitatively accounting for uncertainty in environmental and agronomic factors that impact the potential effects of pesticide use on endangered species. The most significant differences between the Step 2 modeling approach demonstrated in this assessment and EPA's Step 2 approach can be categorized as follows:

- Species relevance: EEC distributions were generated specific to each species range assessed and for each aquatic habitat bin the species occupies. This addressed the uncertainty in EPA modeling that assigned the same EECs to all species within a given HUC2, regardless of the location of that species range relative to cropping patterns. A rigorous assessment of crop proximity and extent around ponds in individual species habitat ranges was conducted by constructing probability distributions of crop configurations (combination of crops). Species-specific crop configurations were used to better simulate the impact of pesticide loadings from spray drift and runoff on exposure concentrations.
- Species exposure relevance: The exposure predictions generated in this assessment were specific to individual species ranges based on the best available species location data. The exposure predictions in EPA's Step 2 analysis were at the HUC2 scale.
- Use of best available spatial data: This assessment used best available crop, soils, and hydrography spatial datasets to characterize the critical exposure-influencing landscape conditions surrounding static water body habitat within species ranges. EPA's assessment used a single representation of landscape conditions per crop group to represent all species habitat within a HUC2 region.
- Agronomic practices: Variability in malathion application timing following regionally specific practices was accounted for in this assessment to achieve a more realistic estimate of resulting exposure. The approach followed by EPA considered only a single application per crop group and HUC2.
- Pesticide use: This assessment included a refinement of the percent treated area based on eight years of recent malathion use data. The EPA's assessment assumed 100% treated area for all crops.
- Probabilistic analysis: The exposure modeling approach used in this assessment incorporated probability distributions of application timing, weather, soil and slope conditions, and crop configurations around ponds to generate 1,000 30-year pond realizations per species, with each realization comprised of 1 to 5 PRZM simulations. EPA's Step 2 modeling for malathion considered just 1 or 2 PRZM/VVWM simulations per crop group within a HUC 2.

The improved spatially explicit, probabilistic aquatic exposure modeling approach resulted in refined yet conservative EECs that for many species were two to three orders of magnitude lower than the EPA Step 2 analysis suggested for species inhabiting static aquatic habitats. These conservative EECs were based on the assumption of 100% PTA for labeled malathion crops. Analysis of historical malathion use data from both EPA (EPA, 2016a) and as part of this study has shown malathion use to cover less than 1% of the dominant crops in the HUC2 05 region. Accounting for actual PTA resulted in more realistic EECs. The probability of maximum 1-day malathion exposure concentrations exceeding a reference concentration of 0.01 µg/L was determined to be between 0.25% and 1.5% depending upon species and habitat characteristics.

The methodology piloted for HUC2 05 is readily reproducible and extendable to assess aquatic species in the remaining HUC2 watersheds across the United States. Although the method provides significant improvements over the draft EPA BE approach, remaining uncertainties may be addressed in future iterations. The approach will continue to evolve as better and more data become available and as computational methods improve. As such, we do not currently support these analyses as a predicate for regulatory action for malathion. We intend to provide our final analyses as part of a refined national endangered species assessment that is currently under development.

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1. INTRODUCTION

The objective of this report is to demonstrate a refined approach to aquatic static water exposure modeling for malathion (MAL) in support of national endangered species effects determinations. The United States (US) Environmental Protection Agency (EPA) has included MAL in an organophosphate (OP) insecticide case study for developing a national procedure for evaluating risks to species listed as threatened or endangered in the United States under the Endangered Species Act (ESA). In April of 2016, the EPA released their complete draft Biological Evaluations (BE) for MAL and two other OP insecticides, chlorpyrifos (CPY), and diazinon (DIA) (EPA, 2016a, b, c). With the BE release, EPA requested suggestions from stakeholders for improving the scientific methods used to predict aquatic exposure, particularly for Step 2 of the BE process when decisions of "likely to adversely affect" or "not likely to adversely affect" are made.

In Step 2 of the Biological Evaluations, the EPA used hydrologic region (HUC2) and crop group specific exposure model scenarios for a collection of different receiving water bodies designed to represent generalized aquatic habitat that species could occupy. The exposure predictions at the HUC2 and crop group level were then used to determine if the pesticide use was likely to adversely affect or not likely to adversely affect each species. FMC, additional registrants, and CropLife America (CLA) have provided extensive comments on the approach that EPA followed in the Step 2 aquatic exposure modeling (Breton et al., 2016). In short, EPA's approach was found to be both technically flawed, overly generalized, overly conservative in its assumptions, and insufficient to produce exposure predictions that could meaningfully be used in identifying species that may be affected by use of the OP insecticides. Aquatic exposure predictions at Step 2 will need to incorporate models, methods, and datasets that allow for a more refined, species-specific prediction of EECs that represents a robust distribution of exposure likelihood that can be used to realistically determine if each species is likely to be adversely affected by the pesticide use. This report presents a pilot Step 2 exposure modeling approach to predict malathion EECs in static water bodies within HUC 2 05, the Ohio River basin.

The refined static water habitat modeling approach demonstrated in this assessment results in malathion concentration predictions relevant to species-specific ranges considering the geographically varying environmental conditions occurring through the range. The aquatic exposure models used include EPA's standard landscape model (Pesticide Root Zone Model (PRZM version 5; Young and Fry, 2014)) and water body model (Variable Volume Water Model (VVWM; Young 2014)). The modeling approach uses probabilistic representations of model input parameters to account for variability and uncertainty in environmental conditions that impact concentrations of malathion in static surface waters potentially inhabited by each species. The approach also takes into account regionally specific agronomic data in determining pesticide application timing and the extent of malathion use on specific crops. The EECs generated following this approach are related back to two of the static habitat "bins" developed by EPA. The resulting probability distributions of exposure concentrations are ready to be used directly in probabilistic risk assessment approaches such as the use of joint probability curves (JPCs) between exposure and species sensitivity distributions (SSDs). The probabilistic, species-specific exposure modeling methodology and subsequent probabilistic risk assessment are directly in agreement with the National Academy of Sciences' National Research Council Panel recommendations on assessing risks to endangered species from pesticides (NRC, 2013), including use of best available spatial data and probabilistic methods.

This pilot assessment addresses all six endangered aquatic species in the crustacean and mollusk taxa that are found in the medium volume (Bin 6) and high volume (Bin 7) aquatic habitats. A third generic aquatic habitat, the low volume water body (Bin 5), has been presented by EPA, however this potential habitat was not addressed in this study. The bin 5 habitat requires a different approach than Bin's 6 and 7 due to its small size, ephemeral nature, and difficulty in robustly delineating its location. The methodology presented incorporates best available spatial datasets to generate realistic exposure model scenario inputs that in turn result in probability distributions of aquatic exposure likelihood that provide a more comprehensive understanding of the potential effects to a specific endangered species based on its range and habitat preferences. This approach is readily transferable to evaluating other aquatic species that inhabit static water bodies across the other HUC2 regions across the US.

2. MATERIALS AND METHODS

2.1. Analysis Plan

2.1.1. Study Area

The modeling approach described in this report was applied to the Ohio River Basin hydrologic unit code (HUC) 2 digit watershed (HUC2 05). The drainage area of the watershed is 421,961 km^2 (162,920 mi^2) and spans across the states of Illinois (6.8%), Indiana (18.2%), Kentucky (23.3%), Maryland (0.3%), New York (1.2%), North Carolina (0.5%), Ohio (18.2%), Pennsylvania (9.6%), Tennessee (6.8%), Virginia (2.5%), and West Virginia (12.7%). The Ohio Basin was selected as a pilot region for several reasons. First, it contains a diversity of environments, including high intensity large scale field crop agriculture, land used for pasture and hay, forested land, and highly developed areas. Both corn and pasture/hay are malathion labeled uses and represent the dominant malathion use crops in the HUC2. The HUC2 05 region was also found to contain multiple aquatic endangered species that inhabit static water bodies. These species include crustaceans and mollusks, some of the most toxicologically sensitive taxa, that are found in medium volume (Bin 6) and high volume (Bin 7) habitats. Finally, the HUC2 05 was also chosen by EPA for piloting their Spatial Aquatic Model (SAM), which is intended to provide spatially explicit pesticide exposure modeling capabilities in the future (EPA, 2015); however, the current version of SAM under development has only addressed exposure in flowing water habitat and has not yet been proposed for addressing static water habitat. Choosing the same location as the SAM model for piloting this refined Step 2 approach will allow for future comparisons between the two methods.

2.1.2. Species Range Identification

A total of six crustaceans and mollusks are found in one or more of the bin 6 and 7 static water habitats. The counties in which these six are known to occur were used to identify the portion of each species range over which aquatic EECs in static water would need to be determined. Table 1 below summarizes these species and the aquatic habitat bins where they are found. Crustaceans and mollusks were targeted in this analysis in anticipation that refinement from Step 1 may be required for the more sensitive taxa.

Table 1. Species and associated EPA habitat Bins evaluated in the HUC2 05 Step 2 analysis.

Taxon	Species Common Name	Species Scientific Name	Bin 6	Bin 7
Crustacean	Kentucky cave shrimp	Palaemonias ganteri	X	X
Crustacean	Madison Cave isopod	Antrolana lira	X	X
Mollusks	Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum		X
Mollusks	Northern riffleshell	Epioblasma torulosa rangiana		X
Mollusks	Rayed bean	Villosa fabalis		X
Mollusks	Snuffbox mussel	Epioblasma triquetra		X

Species range data was provided in a Geographical Information System format by the FIFRA Endangered Species Task Force (FESTF). FESTF gathered information on habitat and occurrence from the Environmental Conservation Online System (ECOS; FWS, 2015), the Information Planning and Conservation (IPaC) database (FWS, 2014), the Critical Habitat Data Portal (FWS, 2015), and the NatureServe database (NatureServe, 2014) for each species record (Frank, 2015). This dataset contains over 100,000 unique species location polygons and is the most comprehensive compilation of spatial endangered species range data currently available.

For the purposes of this aquatic exposure assessment, catchments (very small watersheds) from the NHDPlus Version 2 (V2) dataset were chosen as a hydrologic unit from which to characterize the extent of species habitat. The NHDPlus V2 dataset (McKay et al., 2012) includes data for over 2 million catchments covering the conterminous US, of which 170,145 fall within the HUC2 05 study area. All NHDPlus catchments that overlap any part of the species range defined by the FESTF range dataset were considered in characterizing exposure for the species. Maps showing these "species catchments" associated with each species range can be found in 0.

The identification of species catchments resulted in specific ranges with a hydrologic context. The identification of species habitat range next went a step further by identifying locations of static water bodies within the NHDPlus species catchments that met the size criteria associated with each generic species habitat bin. The high resolution, 1:24,000 scale NHD GIS dataset (USGS, 2014) was used to spatially locate these static water bodies. NHD waterbodies with the following feature codes (FCodes) were selected to be included as potential habitat analysis: 39004 (Lake/Pond: Hydrographic Category = Perennial), 39009 (Lake/Pond: Hydrographic Category = Perennial; Stage = Average Water Elev), 39010 (Lake/Pond: Hydrographic Category = Perennial; Stage = Normal Pool), 39011 (Lake/Pond: Hydrographic Category = Perennial; Stage = Date of Photography), and 39012 (Lake/Pond: Hydrographic Category = Perennial; Stage = Spillway). This resulting collection of NHD ponds was then partitioned into groups associated with the medium volume (Bin 6) and high volume (Bin 7) habitat. (The low volume habitat (Bin 5) was too small to be represented in the NHD and requires a refined approach outside of the scope of this work). However, it should be notes that the low end of the Bin 6 volume and surface area is equivalent to the high end of the Bin 5 habitat. Thus exposure prediction for Bin 6 habitat will be relevant to some Bin 5 species. The partitioning of NHD ponds to habitat bins was based on the surface area of the pond as depicted in the NHD dataset. The pond surface area ranges were set as follows:

- Bin 6: 0.01 – 1.0 ha
- Bin 7: 1.0 – 10 ha

The low end of the range for each habitat bin corresponds to the surface areas for the habitat that were provided in EPA's Step 2 modeling in the BEs. The upper and of the surface area range for Bin 6 is the same as low end of the surface area range for Bin 7, both of which are equivalent to a volume of 20,000 m^3, and are consistent with the volume range defined for the habitat bin (EPA, 2016a). The high end of the surface area range for Bin 7 was set to 10 times higher than the low end of the range. Because a maximum volume or surface area for Bin 7 habitats was not defined by EPA and the Services, selection of ponds spanning a 10-fold range in size was determined to be appropriate and conservative to represent this habitat bin.

For any given species, all ponds falling within the species catchments of interest were assigned as representative of a static water habitat for that species. A summary of the counts of total ponds within species catchments and those ponds near crop are summarized in Table 2. Ponds "near crop" are those that fall within a maximum distance from which spray drift could potentially contribute to exposure. This distance was set to 792 meters, the maximum distance out to which the AgDRIFT model makes predictions of deposition for aerial applications. Any ponds within this distance to malathion treated crops are potentially exposed to malathion. In Table 2, the potential ponds exposed data shows that for all but two species (the Green blossom and Madison Cave isopod), more than 90% of the ponds have some malathion treated crop within 792 meters. This is a strong indication of the broad extent of agriculture within these endangered species ranges.

Table 2. Summary of ponds used to characterize each species by habitat bin.

Species Common Name	Species Scientific Name	Habitat Bin	Total Number of Ponds	Ponds Near Crops	Potential Ponds Exposed (%)
Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum	7	53	41	77.36
Kentucky cave shrimp	Palaemonias ganteri	6	25043	24757	98.86
Kentucky cave shrimp	Palaemonias ganteri	7	512	505	98.63
Madison Cave isopod[1]	Antrolana lira	6/7	101	88	87.13
Northern riffleshell	Epioblasma torulosa rangiana	7	1412	1350	95.61
Rayed bean	Villosa fabalis	7	1459	1369	93.83
Snuffbox mussel	Epioblasma triquetra	7	2001	1875	93.70

1. No bin 7 ponds were identified for this species so the bin 6 ponds were used as surrogates for the purpose of characterizing percent of use sites near ponds.

Identification of representative aquatic habitat areas for each species was essential to characterize the geographically and biologically relevant environmental conditions for modeling potential malathion exposure. In addition to focusing the analysis to relevant areas, locating ponds with surface areas in the range of the relevant pond classes provided the basis for proximity to agricultural crops needed for spray drift deposition calculations. Identification of surrounding watersheds determined the relevant area for characterization of runoff-related environmental conditions.

2.1.3. Modeling Approach

Predictions of malathion concentrations in the species habitat ranges identified above were made by parameterizing agricultural field (PRZM) and surface water (VVWM) model inputs with characteristics observed in the habitat. For each species, a simulation ensemble (a collection of simulations with input parameters randomly sampled based on observed distributions) was computed.

The modeling goal was to define comprehensive yet conservative ranges and frequencies of exposure concentrations in species habitat associated with potential malathion agricultural use sites. PRZM5/VVWM input parameters related to conditions that directly impact potential endangered species aquatic habitat exposure to malathion were defined probabilistically based on the best available national spatial datasets. Probability distributions were developed for: application timing, weather, soil characteristics, and crop configuration around the water body. The quantification of probabilistic inputs in this assessment was based on the analysis of actual ponds and their approximate watersheds within each species habitat range. The general approach for defining the probability distributions for PRZM5 and VVWM inputs was as follows:

- Application Date: A uniform distribution of application dates was defined by the emergence to harvest interval for the crop(s) of interest, taking into account any restricted days before harvest per product labels.
- Weather Time Series: A distribution of EPA's Solar and Meteorological Surface Observation Network (SAMSON; CEAM 2006) stations was defined by calculating likelihood weights as the fraction of cropped area in each species range in each station's approximate region of influence.
- Soils: A distribution of soil profiles representative of the Soil Survey Geographic (SSURGO) database, where soil components were grouped by like parameters, was constructed based on the fraction of a species range overlapping with each soil group.
- Crop Configuration: A distribution of unique combinations of cropped areas and spray drift fractions of an application rate were developed from observations of the actual proportion of crops and

proximity of crops to water bodies in an approximate watershed. A set of cropped area fractions in a watershed and corresponding spray drift fractions comprised one crop configuration.

These probability distributions were randomly sampled to create ensembles of model simulations where each realization represented a possible environmental configuration in a species habitat range. A Latin Hypercube Sampling strategy was used to ensure that each input distribution was sampled to sufficiently capture the input variability.

One randomly selected combination of soil profile, weather station, application date pattern, and crop configuration was used to characterize a set of PRZM simulations (one for each crop in the configuration). The resulting set of runoff, erosion, and malathion loadings from PRZM were weighted by the corresponding cropped area fractions and summed to provide the total loading generated by a given watershed. The total loading to the water body was subsequently used as input to VVWM. Spray drift loading to VVWM was also determined from the proximity of each crop in the configuration to the water body and similarly weighted by the cropped fraction. The coupling of one or more PRZM simulations to a VVWM simulation composed one realization in the simulation ensemble.

The ensemble simulation results, which represent concentrations in exposed ponds only, were combined with the ponds that were not located near crops, and therefore had zero exposure, to derive the overall distribution of estimated environmental concentrations (EEC) and their probability of occurrence for each species. Probability weights on the modeling results in the overall distributions account for the proportion of ponds exposed (near crop) and not exposed (far from crop) provided in Table 2 for each species.

The next section provides a brief overview of the models followed by detailed discussion on the development of probability distributions for key inputs to PRZM and VVWM.

2.1.4. Model Descriptions

This exposure assessment used the most recent EPA standard regulatory models (PRZM5, VVWM, AGDISP). These are described in this section.

The Pesticide in Water Calculator (PWC) (Young, 2015) was released by the US EPA in December of 2015. The PWC model is a shell for running the Pesticide Root Zone Model version 5 (PRZM5; Young and Fry, 2014) and the Variable Volume Water Model (VVWM; Young, 2014). The PRZM5 and VVWM model versions, v5.02 and v1.02 respectively, released with the PWC version 1.50 shell were used in this assessment.

PRZM5 is a one-dimensional, finite-difference model of the vertical soil profile in the crop root zone. It includes processes for pesticide transformation via degradation, hydrolysis and volatilization, and pesticide transport via infiltration, erosion and runoff. PRZM5 accounts for the impact of the landscape (soil, slope, land cover), weather (precipitation, evapotranspiration, temperature), and agricultural practices (application pattern, irrigation, crop practice factors) on these processes. Pesticide loadings in erosion and runoff predicted by PRZM5 are provided as inputs to VVWM.

VVWM is a receiving water model that predicts concentrations of pesticide in two well-mixed regions: a limnetic/water column region and a benthic/bed sediment region. Within each region, pesticide may reside in various phases at equilibrium including freely-dissolved, adsorbed to dissolved organic carbon, adsorbed to suspended or bed sediment, or adsorbed to aquatic plants. VVWM accounts for a daily mass balance of pesticide that includes addition of pesticide, internal exchanges of pesticide between phases and regions, and transformation or removal of pesticide. Pesticide may enter the system by deposition of spray drift or carried by runoff and eroded sediment. Pesticide may exit the system by transformation via degradation, hydrolysis, or volatilization. VVWM has several advanced options including: simulation of pesticide removal by overflow, simulation of pesticide losses to burial in bed sediment, and simulation of a variable volume water column. However, these options were not enabled for this assessment. Pesticide burial and overflow were omitted to generate more conservative concentration predictions. Variable water volume was not simulated so that the vernal pool volume could be simulated at various constant volume estimates based on observed surface areas and assumed depths.

The AGDISP version 8.26 (Bilanin et al., 1989; Teske and Curbishley, 2011) is EPA's current standard tier III model for calculating spray drift contributions to exposure. AGDISP, which was initially developed by National Aeronautics and Space Administration, the USDA Forest Service, and the U.S. Army, includes models for simulating drift from aerial pesticide applications. AGDISP, under default settings, provides aerial drift fraction estimates up to 2500 ft, from the use site. In contrast, the tier I drift models in AgDRIFT are limited to 1000 ft only. Once the drift curve is set up in AGDISP, the water body-integrated drift fraction for custom water bodies can be calculated. The use of AGDISP in calculating aerial spray drift curves for exposure modeling, including the setting up of malathion specific tank mixes, is described in detail in Section 2.2.6.2.

2.2. Development of Model Inputs

Probability distributions of several model inputs associated with landscape characteristics specific to each species range and pesticide application timing were developed. These model inputs included weather, soil characteristics, application timing, spray drift fraction, and cropped fraction of drainage area or percent cropped area (PCA). These inputs were chosen because they are important factors in determining the variability in magnitude and timing of exposure produced by runoff and spray drift. Furthermore, high resolution spatial datasets required to characterize these key inputs are readily available at the national scale.

Additional inputs were modeled deterministically (held constant by crop or across all simulations) such as land cover curve numbers, crop growth parameters, dimensions of habitat bins and watersheds, and environmental fate parameters. Methods for deriving both probabilistic and deterministic inputs are described in this section.

2.2.1. Malathion Environmental Fate

The malathion environmental fate model inputs used in the Step 2 refined modeling were the same as those used in the Step 1 aquatic exposure modeling (Teed et al., 2016). These parameters are summarized here in Table 3.

Table 3. Malathion environmental fate parameters for aquatic exposure modeling.

Model Parameter	Value	Reference [MRID]
Koc (mL/g)	217	Blumhorst, 1989 [41345201]
Aerobic aquatic metabolism half-life (days)	3.4	Blumhorst, 1991a [41721601]; Knoch, 2001a [46769502]; Hiler and Mannella, 2012 [48906401]
Water reference temperature (°C)	20	-
Anaerobic aquatic metabolism half-life (days)	7.5	3x mean value; Blumhorst, 1991b [42216301]
Benthic reference temperature (°C)	20	-

Aqueous photolysis half-life (days)	156	Carpenter, 1990 [41673001]
Aerobic soil half-life (days)	0.24	Blumhorst, 1990 [41721701]; Knoch, 2001b [46769501]; Nixon, 1995 [43868601]
Soil reference temperature (°C)	20	-
Hydrolysis half-life (days)	6.21	Teeter, 1988 [40941201]
Molecular weight (g/mol)	330.36	-
Vapor pressure (torr)	4.0 x10-5	Cheminova A/S, 1988 [40966603]
Solubility (mg/L)	145	Cheminova A/S, 1988 [40966603]
Foliar degradation (days)	4.1 (non-ULV); 5.7 (ULV)	Moore et al., 2014. [49389301]
Application efficiency (ground/aerial)	0.99/0.95	EPA, 2009

2.2.2. Malathion Crop Footprint Development

Characterization of crop extent and associated pesticide potential use is an important step in understanding the potential risk for chemical exposure to endangered species and the habitat on which they depend. Pesticide labels provide information that describes the crops and land uses where that pesticide can potentially be applied. When coupled with spatial datasets of land cover and crop extents, pesticide labels can be used to determine the geographic extent of potential use sites for the pesticide. The crop footprint for a pesticide represents an estimate of the maximum areal extent of where applications could occur. Crop location information is used to understand the magnitude of drift deposition, percent cropped area to scale drift and runoff, and to select relevant soils and environmental conditions in the habitat.

A footprint of malathion agricultural use sites developed using the most recent five years (2011 – 2015) of the NASS Cropland Data Layer (CDL) (USDA, 2011-2015) and the 2011 National Land Over Dataset (NLCD) (Xian et al., 2011).The CDL includes classification for 126 crops and is published on a yearly basis. The NLCD is published once every 5 years and contains a total of 20 land cover classes, two of which are planted or cultivated ("Pasture/Hay" and "Cultivated Crops"). The malathion crop footprint was developed in following steps:

1. A crosswalk between the CDL classes and malathion-specific crop groups was created. The malathion agricultural use crop groups that were considered in this assessment included: corn, cotton, orchards and grapes, other crops, other grains, other row crops, rice, vegetables and groups fruit, wheat, and pasture/hay/forage. The crosswalk was based on EPAs crosswalk used to develop crop group footprints for the BEs (EPA, 2016a), with the primary exception being that specific CDL cop classes not labeled for malathion use were excluded from the crop group. Table 4 provides the details of this modified crosswalk.
2. The five years of CDL (2011-2015) were then overlaid using a GIS raster "Combine" operation and the dominant CDL class from the five years was assigned to each pixel. If a dominant pixel from the five years did not exist, then the CDL class from 2015 was selected to represent the crop class for that pixel.
3. Based on the dominant crop class, each pixel was classified into 10 of the malathion agricultural crop groups.
4. The NLCD 2011 dataset was brought into the development of malathion crop footprint to improve the delineation of the pasture/hay crop group use sites. The 2011 NLCD distinguishes between planted/cultivated pasture/hay and un-managed grassland. Beginning in 2014, the CDL began

combining multiple pasture and hay related classes with the "grassland herbaceous" class. Because the dominant malathion use is on managed pasture/hay, the NLCD 2011 was incorporated to distinguish these areas from unmanaged grasslands. This was done by reclassifying any pixel with a dominant CDL class of pasture/hay based on the CDL/malathion crop group crosswalk to pasture/hay ONLY if the NLCD 2011 was also classified as pasture/hay. Other pixels classified as pasture/hay based on the dominant CDL class, but not classified by NLCD 2011 as pasture/hay, were classified as "untreated pasture".

The malathion crop footprint for HUC2 05 is shown in Figure 1. The dominant crop groups across the HUC2 are pasture/hay, followed by corn and wheat.

Table 4. Crosswalk between malathion treated crops and crop groups.

CDL Class Name	CDL Value	Crop Group	CDL Class Name	CDL Value	Crop Group
Corn	1	Corn	Mustard	35	vegetable and ground fruit
Dbl Crop Oats/Corn	226	Corn	Potatoes	43	vegetable and ground fruit
Dbl Crop Barley/Corn	237	Corn	Dry Beans	42	vegetable and ground fruit
Dbl Crop Corn/Soybeans	241	Corn	Dbl Crop Lettuce/Barley	233	vegetable and ground fruit
Dbl Crop WinWht/Corn	225	Corn	Peppers	216	vegetable and ground fruit
Cotton	2	Cotton	Broccoli	214	vegetable and ground fruit
Dbl Crop WinWht/Cotton	238	Cotton	Garlic	208	vegetable and ground fruit
Dbl Crop Lettuce/Cotton	232	Cotton	Carrots	206	vegetable and ground fruit
Dbl Crop Soybeans/Cotton	239	Cotton	Pop or Orn Corn	13	vegetable and ground fruit
Citrus	72	Orchards and grapes	Mint	14	vegetable and ground fruit
Olives	211	Orchards and grapes	Asparagus	207	vegetable and ground fruit
Pears	77	Orchards and grapes	Honeydew Melons	213	vegetable and ground fruit
Oranges	212	Orchards and grapes	Greens	219	vegetable and ground fruit
Pecans	74	Orchards and grapes	Cantaloupes	209	vegetable and ground fruit
Grapes	69	Orchards and grapes	Sweet Corn	12	vegetable and ground fruit
Other Tree Crops	71	Orchards and grapes	Cauliflower	244	vegetable and ground fruit
Apples	68	Orchards and grapes	Turnips	247	vegetable and ground fruit
Peaches	67	Orchards and grapes	Radishes	246	vegetable and ground fruit
Cherries	66	Orchards and grapes	Celery	245	vegetable and ground fruit
Walnuts	76	Orchards and grapes	Lettuce	227	vegetable and ground fruit
Apricots	223	Orchards and grapes	Pumpkins	229	vegetable and ground fruit
Nectarines	218	Orchards and grapes	Dbl Crop Lettuce/Durum Wht	230	vegetable and ground fruit
Clover/Wildflowers	58	Other Crops	Sweet Potatoes	46	vegetable and ground fruit
Sod/Grass Seed	59	Other Crops	Dbl Crop Lettuce/Cantaloupe	231	vegetable and ground fruit
Other Crops	44	Other Crops	Cabbage	243	vegetable and ground fruit
Dbl Crop Soybeans/Oats	240	Other grains	Blueberries	242	vegetable and ground fruit
Rye	27	Other grains	Squash	222	vegetable and ground fruit
Oats	28	Other grains	Chick Peas	51	vegetable and ground fruit
Flaxseed	32	Other grains	Misc Vegs & Fruits	47	vegetable and ground fruit
Dbl Crop Barley/Soybeans	254	Other grains	Eggplants	248	vegetable and ground fruit
Dbl Crop Barley/Sorghum	235	Other grains	Watermelons	48	vegetable and ground fruit
Barley	21	Other grains	Onions	49	vegetable and ground fruit
Sorghum	4	Other grains	Cucumbers	50	vegetable and ground fruit
Other Small Grains	25	Other grains	Strawberries	221	vegetable and ground fruit
Hops	56	Other row crops	Peas	53	vegetable and ground fruit
Rice	3	Rice	Tomatoes	54	vegetable and ground fruit
Pasture/Grass[1]	62	Pasture/hay/forage	Caneberries	55	vegetable and ground fruit

CDL Class Name	CDL Value	Crop Group	CDL Class Name	CDL Value	Crop Group
Switchgrass[1]	60	Pasture/hay/forage	Herbs	57	vegetable and ground fruit
Other Hay/Non Alfalfa[1]	37	Pasture/hay/forage	Winter Wheat	24	Wheat
Alfalfa[1]	36	Pasture/hay/forage	Spring Wheat	23	Wheat
Vetch[1]	224	Pasture/hay/forage	Durum Wheat	22	Wheat
Grassland Herbaceous[1]	171	Pasture/hay/forage	Dbl Crop WinWht/Soybeans	26	Wheat
Grassland/pasture[1]	176	Pasture/hay/forage	Dbl Crop Durum Wht/Sorghum	234	Wheat
Pasture/Hay[1]	181	Pasture/hay/forage	Dbl Crop WinWht/Sorghum	236	Wheat

1. Group class dependent upon NLCD 2011 classfification as "Pasture/hay"

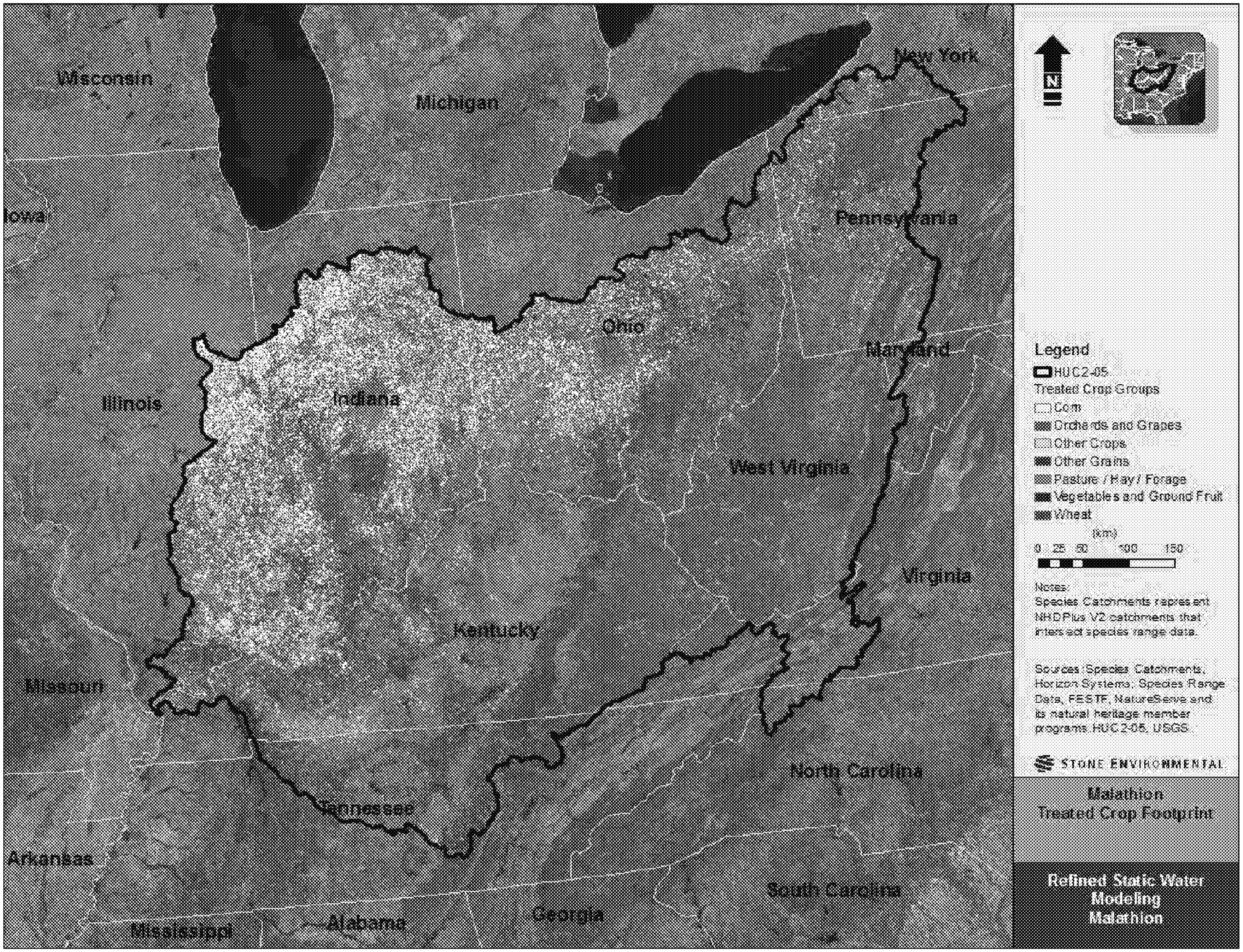

Figure 1. Malathion-treated crop footprint.

2.2.3. Application Inputs

Concentration predictions are sensitive to the magnitude and timing of pesticide applications. Application method, rate, and efficiency impact both the overall pesticide mass deposited onto the receiving field and the mass that may be deposited directly into nearby water bodies via spray drift or runoff. Application timing relative to rainfall impacts the pesticide mass on crop foliage or in soil that has potential to travel off the field dissolved in runoff water or adsorbed to eroded soil. To capture the full range of pesticide concentrations in receiving waters and their likelihood, it is important to sample the range of potential/likely application patterns in model simulations.

The highest Cheminova malathion 57% labeled application rate for crops in HUC2 05 were assumed in all simulations. The maximum number of applications at the minimum interval permitted by the label to reach the annual total use rate were applied in all simulations. In all cases, the applications were foliar and the method was aerial assuming 95% efficiency. The rate, interval and number of applications relevant to HUC2 05 are summarized in (Table 5).

The first application day in the series was determined probabilistically. An index into the likely time window of applications was sampled according to a uniform distribution (all days in the window being equally likely) to determine the first application date. Likely application windows were based on review of agricultural cooperative extension service documents and electronic communication with extension specialists and entomologists in the states of Indiana, Illinois, Kentucky, Ohio, Pennsylvania, and Tennessee. Usual planting and harvesting dates and production maps for these states were also used to establish date ranges for the growing seasons (USDA NASS, 2010; USDA OCE, 2012).

Malathion product label information on pre-harvest intervals and pest-specific application instructions was also taken into account and cross-referenced with other information sources on target pests and application timing. For some of the crop use patterns that have minimal production in this region, extension experts indicated that they had little knowledge of when malathion would be applied. Therefore, the estimated application window date ranges should be seen as general times when malathion could potentially be applied in HUC2 05, even though these applications may occur infrequently for some of these crop use patterns. This literature review and other communication provided a preliminary application window (Table 5). Preliminary windows were then adjusted for emergence and harvest dates from PRZM scenarios to ensure that applications were modeled during the growing period of the simulation. More detailed information on how each application window was derived is available in Appendix B.

Table 5. Summary of malathion application assumptions.

Crop Group	Highest Rate Crop on Label	Max Single App. Rate (kg/ha)	Apps per Year	Interval (d)	Method	Efficiency	Type
Corn	Corn	1.121	2	5	Aerial	95%	Foliar
Cotton	Cotton	2.802	3	7	Aerial	95%	Foliar
Orchards/grapes	Peaches	3.363	3	11	Aerial	95%	Foliar
Other crops	Clover	1.401	6	14	Aerial	95%	Foliar
Other grains	Rye	1.121	3	7	Aerial	95%	Foliar
Other row crops	Hops	0.706	3	7	Aerial	95%	Foliar
Pasture/hay/forage	Alfalfa	1.401	6	14	Aerial	95%	Foliar

Vegetables and ground fruit	Strawberries	2.242	4	7	Aerial	95%	Foliar
Wheat	Wheat	1.121	2	7	Aerial	95%	Foliar

Table 6. MAL application window in Ohio River basin based on literature review and personal communications.

Crop Group	Highest Rate Crop on Label	Application Window	Window Adjusted for Emergence/Harvest	PRZM Scenario
Corn	Corn	1 May-1 Oct	1 May-1 Oct	OHCornSTD
Cotton	Cotton	1 Jul-1 Nov	1 Jul-1 Nov	NCcottonSTD
Orchards/grapes	Peaches	10 May-25 Aug	10 May-25 Aug	NCappleSTD
Other crops	Clover	7 Apr-15 Sep	7 Apr-30 Jun	ORgrassseedSTD
Other grains	Rye	1 Apr-1 Jun	20 May-1 Jun	KSsorghumSTD
Other row crops	Hops	1 May-1 Sep	16 May-1 Sep	NCpeanutSTD
Pasture/hay/forage	Alfalfa	7 Apr-15 Sep	7 Apr-28 Aug	NCalfalfaOP
Vegetables and ground fruit	Strawberries	15 Apr-15 May	16-Jun 2 Sep	ILbeansNMC
Wheat	Wheat	1 May-1 Jul	20 May-1 Jul	KSsorghumSTD

For model realizations with more than one crop in the crop configuration around the pond, the random index would be used to lookup the first application date in the application window for each crop. For example, in a pond watershed with both corn and wheat, an index of 7 would result in applications on corn starting on May 7 and applications on wheat starting on May 26.

2.2.4. Weather Analysis

Precipitation, evapotranspiration, and atmospheric temperature, which vary throughout the geographically wide species habitat range, are critical model inputs for pesticide fate and transport. These weather parameters influence soil moisture, erosion, and runoff as well as the pesticide degradation rate. To determine weather time-series relevant for each species, Thiessen polygons generated for all SAMSON (CEAM, 2006) weather stations nationwide were intersected with treated crop area in each species range in HUC2 05. The crop area associated with each weather station corresponded to the probability that the weather time series would be sampled in the simulation ensembles. The probability associated with each species and weather station is provided in (Table 7).

Table 7. Weather station distribution by species.

Species Common Name	Species Scientific Name	Weather Station (ID)	Area-Weighted Probability
Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum	Bristol, TN (W13877)	37.51%
Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum	Charleston, WV (W13866)	0.23%
Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum	Roanoke, VA (W13741)	62.27%
Kentucky cave shrimp	Palaemonias ganteri	Evansville, IN (W93817)	3.10%
Kentucky cave shrimp	Palaemonias ganteri	Lexington, KY (W93820)	0.49%
Kentucky cave shrimp	Palaemonias ganteri	Louisville, KY (W93821)	42.25%
Kentucky cave shrimp	Palaemonias ganteri	Nashville, TN (W13897)	54.16%

Species Common Name	Species Scientific Name	Weather Station (ID)	Area-Weighted Probability
Madison Cave isopod	Antrolana lira	Elkins, WV (W13729)	20.63%
Madison Cave isopod	Antrolana lira	Roanoke, VA (W13741)	79.37%
Northern riffleshell	Epioblasma torulosa rangiana	Bradford, PA (W04751)	3.36%
Northern riffleshell	Epioblasma torulosa rangiana	Charleston, WV (W13866)	0.48%
Northern riffleshell	Epioblasma torulosa rangiana	Columbus, OH (W14821)	11.06%
Northern riffleshell	Epioblasma torulosa rangiana	Covington (Cincinnati), KY (W93814)	0.03%
Northern riffleshell	Epioblasma torulosa rangiana	Dayton, OH (W93815)	0.25%
Northern riffleshell	Epioblasma torulosa rangiana	Elkins, WV (W13729)	0.44%
Northern riffleshell	Epioblasma torulosa rangiana	Erie, PA (W14860)	9.04%
Northern riffleshell	Epioblasma torulosa rangiana	Evansville, IN (W93817)	1.47%
Northern riffleshell	Epioblasma torulosa rangiana	Fort Wayne, IN (W14827)	1.09%
Northern riffleshell	Epioblasma torulosa rangiana	Huntington, WV (W03860)	8.48%
Northern riffleshell	Epioblasma torulosa rangiana	Indianapolis, IN (W93819)	2.06%
Northern riffleshell	Epioblasma torulosa rangiana	Lexington, KY (W93820)	0.08%
Northern riffleshell	Epioblasma torulosa rangiana	Louisville, KY (W93821)	6.53%
Northern riffleshell	Epioblasma torulosa rangiana	Nashville, TN (W13897)	35.35%
Northern riffleshell	Epioblasma torulosa rangiana	Pittsburgh, PA (W94823)	7.58%
Northern riffleshell	Epioblasma torulosa rangiana	South Bend, IN (W14848)	1.87%
Northern riffleshell	Epioblasma torulosa rangiana	Youngstown, OH (W14852)	10.83%
Rayed bean	Villosa fabalis	Bradford, PA (W04751)	3.42%
Rayed bean	Villosa fabalis	Bristol, TN (W13877)	2.26%
Rayed bean	Villosa fabalis	Charleston, WV (W13866)	0.85%
Rayed bean	Villosa fabalis	Columbus, OH (W14821)	3.72%
Rayed bean	Villosa fabalis	Covington (Cincinnati), KY (W93814)	10.84%
Rayed bean	Villosa fabalis	Dayton, OH (W93815)	37.21%
Rayed bean	Villosa fabalis	Elkins, WV (W13729)	1.53%
Rayed bean	Villosa fabalis	Erie, PA (W14860)	8.88%
Rayed bean	Villosa fabalis	Fort Wayne, IN (W14827)	0.24%
Rayed bean	Villosa fabalis	Huntington, WV (W03860)	8.06%
Rayed bean	Villosa fabalis	Indianapolis, IN (W93819)	0.20%
Rayed bean	Villosa fabalis	Lexington, KY (W93820)	2.48%
Rayed bean	Villosa fabalis	Louisville, KY (W93821)	0.04%
Rayed bean	Villosa fabalis	Mansfield, OH (W14891)	0.43%
Rayed bean	Villosa fabalis	Pittsburgh, PA (W94823)	7.51%
Rayed bean	Villosa fabalis	Roanoke, VA (W13741)	0.48%
Rayed bean	Villosa fabalis	South Bend, IN (W14848)	1.20%
Rayed bean	Villosa fabalis	Youngstown, OH (W14852)	10.63%
Snuffbox mussel	Epioblasma triquetra	Akron/Canton, OH (W14895)	0.02%
Snuffbox mussel	Epioblasma triquetra	Bradford, PA (W04751)	1.86%
Snuffbox mussel	Epioblasma triquetra	Bristol, TN (W13877)	3.60%
Snuffbox mussel	Epioblasma triquetra	Charleston, WV (W13866)	5.91%
Snuffbox mussel	Epioblasma triquetra	Chattanooga, TN (W13882)	0.00%

Species Common Name	Species Scientific Name	Weather Station (ID)	Area-Weighted Probability
Snuffbox mussel	Epioblasma triquetra	Columbus, OH (W14821)	2.15%
Snuffbox mussel	Epioblasma triquetra	Covington (Cincinnati), KY (W93814)	12.51%
Snuffbox mussel	Epioblasma triquetra	Dayton, OH (W93815)	4.89%
Snuffbox mussel	Epioblasma triquetra	Elkins, WV (W13729)	3.84%
Snuffbox mussel	Epioblasma triquetra	Erie, PA (W14860)	6.56%
Snuffbox mussel	Epioblasma triquetra	Evansville, IN (W93817)	1.26%
Snuffbox mussel	Epioblasma triquetra	Fort Wayne, IN (W14827)	1.47%
Snuffbox mussel	Epioblasma triquetra	Huntington, WV (W03860)	7.88%
Snuffbox mussel	Epioblasma triquetra	Indianapolis, IN (W93819)	2.34%
Snuffbox mussel	Epioblasma triquetra	Knoxville, TN (W13891)	0.07%
Snuffbox mussel	Epioblasma triquetra	Lexington, KY (W93820)	3.18%
Snuffbox mussel	Epioblasma triquetra	Louisville, KY (W93821)	1.35%
Snuffbox mussel	Epioblasma triquetra	Mansfield, OH (W14891)	0.17%
Snuffbox mussel	Epioblasma triquetra	Nashville, TN (W13897)	0.23%
Snuffbox mussel	Epioblasma triquetra	Pittsburgh, PA (W94823)	22.20%
Snuffbox mussel	Epioblasma triquetra	Roanoke, VA (W13741)	5.89%
Snuffbox mussel	Epioblasma triquetra	South Bend, IN (W14848)	0.28%
Snuffbox mussel	Epioblasma triquetra	Springfield, IL (W93822)	3.57%
Snuffbox mussel	Epioblasma triquetra	Youngstown, OH (W14852)	8.76%

2.2.5. Soils Analysis

Soil properties related to runoff/erosion potential and chemical adsorption are important factors in predicting pesticide concentrations in nearby receiving waters. To capture the varied impacts of soils on concentration predictions, it is important to characterize the distribution, including the range and likelihood of occurrence, of different soils throughout the species habitat range.

Soil properties strongly correlated with runoff and erosion potential were evaluated for cropped areas within species ranges. Soils were classified into similar groups based on the values of four key properties in order to simplify the number of unique soils to model. These soil properties: hydrologic group, erodibility, organic carbon, and land slope, are listed in Table 8. The dominant soil component in a group, based on the total area of each soil component co-occurring with treated crops in all combined species ranges, was selected to represent the group for modeling. The relative areas corresponding to each soil group for specific species ranges were used to build species-specific probability distributions to determine the frequency with which the different soil components were represented in model simulations.

Besides the four key group properties, additional soil parameters needed for PRZM model inputs, listed in Table 9, were derived from the soil group's representative component. Details on the approach to grouping like soils, selecting a group's representative component, and determining the probability of occurrence by area are described below.

Soil data were extracted using the best available digital soils database, the NRCS Soil Survey Geographic (SSURGO) Database (NRCS, 2015). The SSURGO database has coverage for most areas within the United States with data collected at scales between 1:12,000 and 1:63,360. The typical minimum mapping unit size is approximately 1 to 10 acres. Each mapping unit consists of one or more soils (components), commonly with one to three soil components per mapping unit. The SSURGO database describes the percent area of the mapping unit that each soil component occupies. In addition, each soil description contains information on multiple layers of the soil, including all the soil properties required as input to the PRZM model.

All soil components within mapping units that overlapped NHDPlus catchments with species range and cropped area with potential for malathion applications were included in the analysis. The area of overlap was calculated by a raster combine operation and multiplied by the component percent to determine the area represented by each component.

Grouping like soils was conducted primarily following the approach outlined by EPA for the Spatial Aquatic Model (SAM) (SAM, 2014). EPA identified the following four parameters as having the biggest impact on runoff and erosion based on the USDA NRCS Water Quality Index (WQI) for runoff from agricultural fields (Lal and McKinney, 2012): soil hydrologic group, Universal Soil Loss Equation (USLE) K factor in the surface horizon, organic carbon percent in the surface horizon, and percent land slope.

Using the same value ranges for these parameters as determined by EPA for use in SAM, shown in Table 8 resulted in 600 unique soil groups. These unique combinations capture a wide range of conditions that are critical for runoff and erosion processes. Each soil component was assigned to a soil group based on the criteria in the table.

Table 8. Soil properties and ranges used to categorize soil groups.

Soil Hydrologic Group	Surface USLE K Factor	Surface Organic Carbon (%)	Land Slope (%)
A	< 0.1	< 0.5	<2
B	0.11 - 0.2	0.5 - 2	5-Feb
C	0.21 - 0.32	4-Feb	10-May
D	0.33 - 0.43	6-Apr	15-Oct
	0.44 - 0.64	8-Jun	>15
		> 8	

One representative component for each group was identified to determine the remaining model input values related to the soil profile. All of the soil inputs for PRZM were derived from the representative component as explained in Table 9, following the same approach used by EPA for SAM with the exception of slope. The EPA method calculated a map-unit-average slope whereas this analysis used the slope from the representative component to preserve complete sets of component attributes.

Identification of the representative component primarily followed the EPA method in a two part process:

- First, the dominant component in each map unit was identified as the component with the majority component percentage belonging to the most common hydrologic group in the map unit. In contrast to the EPA method, for components with a drained and un-drained hydrologic group, the drained hydrologic group was assumed because drainage is more likely to be used in agricultural areas to support optimal crop growth. The dominant component for each map unit was assigned to the 600 unique soil groups. Components missing one of the four key parameters for grouping were not assigned to groups.

- Next, the component with the highest area and without missing data was selected as the representative component of the group. Both component level and horizon level attributes from the representative component were used to derive model input values following the calculations summarized in Table 9. Horizon-level attributes were simplified to two horizons, surface (0-10 cm) and subsurface (> 10 cm), by depth weighted averaging, following the EPA SAM approach. Components without at least one horizon in the surface and subsurface depth ranges or with incomplete horizon data that could not be estimated from other parameters were not evaluated. For horizons that were missing bulk density, wilting point, or field capacity data and had sand and clay composition data, the missing parameter could be estimated using empirical relationships defined in the PRZM manual (Suárez, 2006). Finally, components were only selected as representatives of soil groups with complete horizon data and a subsurface horizon depth greater than 30 cm. Subsurface horizons extending below 30 cm but not deeper than the maximum crop rooting depth were extrapolated to the root depth plus a buffer of 1 cm.

Through the soil analysis and by grouping on key parameters, 292 unique groups of the 600 possible were represented in species ranges. Individual species ranges were comprised of a minimum of 42 unique soil groups (Madison Cave isopod) up to 227 groups for one of the larger ranges (Snuffbox mussel). The distribution of these soils corresponding to the different hydrogroups and land slope classes is shown in (Table 10). The more runoff-prone C and D soils represented 19-50% and 10-20% of the species ranges, respectively. Slopes varied across all slope classes for all species with slopes less than or equal to 10% the most common.

For each species, a probability distribution of the soil groups was generated by calculating the area fraction representation of each soil group in the NHDPlus catchments with species range overlap. The total area of the soil components in each group out of the total area of all groups determined the group's likelihood of occurrence, and the likelihood the soil group would be represented in a PRZM simulation.

Table 9. Soil properties required by PRZM and related data sources.

Parameter	SWCC Parameter or Modeling Use	SSURGO Table	SSURGO Attribute	Calculation
Hydrologic Soil Group	Determination of Curve Number	component	hydgrp	Use the drained hydro group for A/D, B/D, C/D (non D). The hydro group with the plurality of component percent is considered dominant group for each map unit.
K Factor	USLE (Universal Soil Loss Equation) K - soil erodibility factor representing soil susceptibility to erosion	chorizon	kwfact	Surface kwfact for representative components
OC Surface Horizon (0-10 cm)	OC % - carbon bound to organic compounds in soil	chorizon	om_r/1.724	Surface om_r for representative components
OC Subsurface Horizon (> 10 cm)	OC % - carbon bound to organic compounds in soil	chorizon	om_r/1.724	Thickness-weighted average om_r for all subsurface horizons for representative components
Slope	Land Slope % and determination of length-slope topographic factor	component	slope_r	From representative components
Slope Length	Determination of length-slope topographic factor	component	slopelenus_r	From representative components or 356.8 m (EPA default for ponds) in cases of missing data
Length-Slope Topographic Factor	USLE LS			Lookup based on slope and slope length from PRZM Manual Table 5.5 (Suarez, 2006)
Runoff Curve Number	CN			Lookup based on hydrologic group and crop using EPA SAM Table 19 (SAM, 2014) cross-reference for cropped and fallow values based on NRCS TR-55 (NRCS, 1986) methodology.
Number of Horizons	Number of Horizons			2 - surface (0-10 cm) and subsurface (> 10 cm)
Thickness Surface Horizon	Thick			10
Thickness Subsurface Horizon	Thick	chorizon	hzdept_r, hzdepb_r	Sum of thicknesses (hzdepb_r-hzdept_r) for all subsurface horizons rounded to nearest even number (for divisibility by 2) for representative components
Bulk Density Surface Horizon	ρ, dry weight per unit volume	chorizon	dbthirdbar_r	Surface dbthirdbar_r for representative components
Bulk Density Subsurface Horizon	ρ, dry weight per unit volume	chorizon	dbthirdbar_r	Thickness-weighted average dbthirdbar_r for all subsurface horizons for representative components
Field Capacity Surface Horizon	Max Cap. (maximum. water retention capacity)	chorizon	wthirdbar_r	Surface wthirdbar_r for representative components
Field Capacity Subsurface Horizon	Max. Cap. (maximum water retention capacity)	chorizon	wthirdbar_r	Thickness-weighted average wthirdbar_r for all subsurface horizons for representative

				components
Wilting Point Surface Horizon	Min. Cap. (minimum water retention capacity)	chorizon	wfifteenbar_r	Surface wfifteenbar_r for representative components
Wilting Point Subsurface Horizon	Min. Cap. (minimum water retention capacity)	chorizon	wfifteenbar_r	Thickness-weighted average wfifteenbar_r for all subsurface horizons for representative components
Number of Compartments in Surface Horizon	N			100
Number of Compartments in Subsurface Horizon	N			Subsurface thickness divided by 2
Runoff Distribution Depth	R-Depth			2 (SWCC default)
Runoff Distribution Decline	R-Decline			1.55 (SWCC default)
Runoff Distribution Efficiency	Efficiency			0.266 (SWCC default)
Erosion Distribution Depth	E-Depth			0.1 (SWCC default)
Erosion Distribution Decline	E-Decline			0 (SWCC default)

Table 10. Hydrologic soil group class and slope class distributions by species range.

Species Common Name	No. Unique Soils	Hydrogroup A	Hydrogroup B	Hydrogroup C	Hydrogroup D	Slope ≤ 2%	Slope > 2% and ≤ 5%	Slope > 5% and ≤ 10%	Slope > 10% and ≤ 15%	Slope > 15%
Madison Cave isopod	42	16.67%	47.62%	23.81%	11.90%	21.43%	14.29%	30.95%	9.52%	23.81%
Green blossom (pearlymussel)	106	29.25%	41.51%	18.87%	10.38%	16.98%	10.38%	21.70%	18.87%	32.08%
Northern riffleshell	198	24.24%	26.26%	29.80%	19.70%	27.27%	14.14%	24.75%	14.65%	19.19%
Kentucky cave shrimp	111	17.12%	32.43%	34.23%	16.22%	18.92%	13.51%	27.03%	14.41%	26.13%
Snuffbox mussel	227	25.99%	28.19%	26.87%	18.94%	23.35%	13.22%	23.79%	16.30%	23.35%
Rayed bean	224	25.89%	26.34%	27.23%	20.54%	26.79%	13.84%	22.32%	15.18%	21.88%

2.2.6. Crop Configuration

Crop configurations are collections of percent cropped areas and spray drift fractions for all of the different crops observed to surround ponds. A distribution of crop configurations is defined for each species range and habitat bin. For bin 6 and 7 habitats, crop configurations were determined for each pond with dimensions matching the habitat bin that corresponded to NHD Plus catchments overlapping each species range. Probability weights in the bin 6 and 7 distributions were uniform (each configuration had equal likelihood). Each configuration could require one or more PRZM simulations depending on the number of crops. The collection of PRZM simulations is part of one model realization in the ensembles of randomly selected input parameter sets.

The crop configuration concept is illustrated in Figure 2 and Table 11 for two ponds classified as habitat bin 6 with unique configurations of crops, percent cropped area (PCA) and spray drift potential. Details on the PCA and spray drift calculations are provided in subsections that follow.

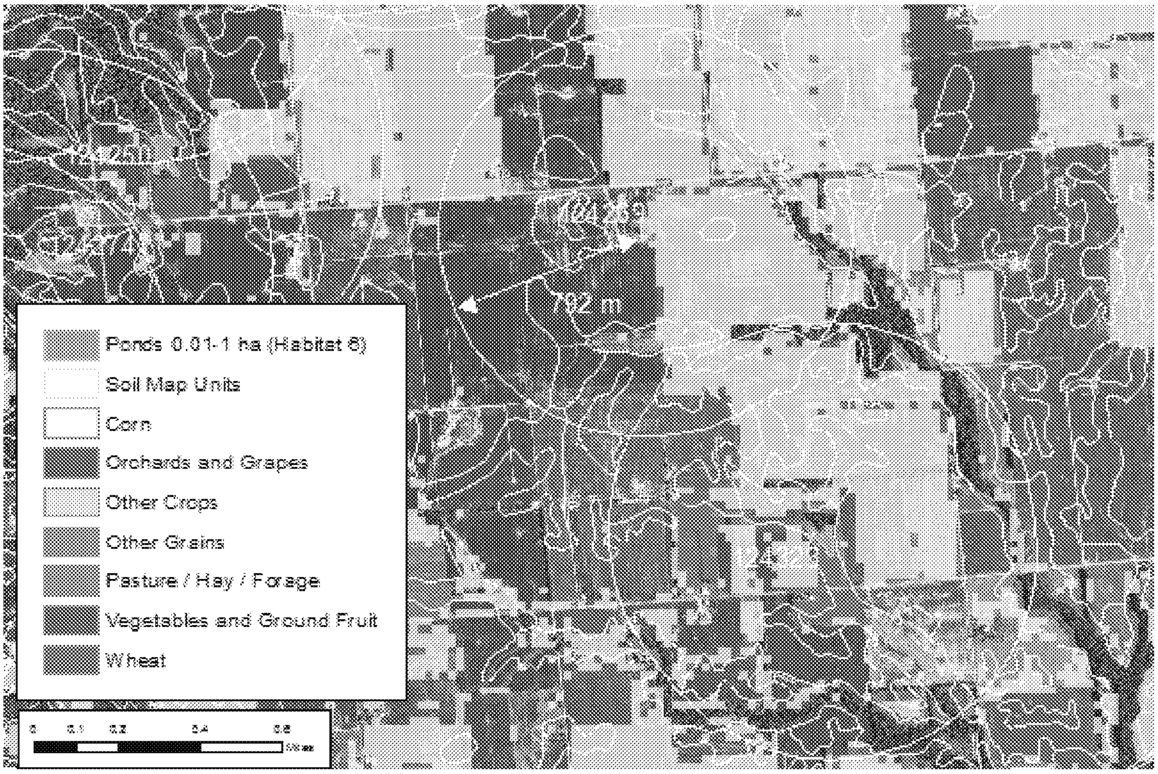

Figure 2. Crop configuration example for two ponds.

Table 11. Crop configuration example tabulation.

Crop Configuration	Pond	Habitat Bin	Crop Group	Percent Cropped Area	Spray Drift
1	124269	6	Corn	48%	15%
2	124323	6	Corn	37%	8%
2	124323	6	Pasture/Hay/Forage	5%	15%

2.2.6.1. Percent Cropped Area

Percent cropped area (PCA), the proportion of crop overlap with the area surrounding a water body, is an important factor in estimating pesticide loadings. Greater extents of crop coverage surrounding the water body have potential for greater off-target pesticide transport. The extent of crop coverage varies widely within species ranges which overlap with agricultural lands, grasslands, and forested areas. Therefore, PCAs of the potentially treated crops around the water bodies in species habitat ranges were calculated and applied as scale factors to PRZM runoff loadings and spray drift inputs.

A PCA was calculated for each crop in the area surrounding a water body and this collection of PCAs comprised an important component of the crop configuration. A representative watershed area for each pond was required as the basis for the PCA calculation. The representative watershed for each pond was assumed to be a 792 m proximity zone around the pond. The 792 meter distance was based on the maximum proximity for potential spray drift exposure. PCA was calculated for each crop as the sum of the crop area in the estimated watershed divided by the total area of the watershed. Figure 3 illustrates PCA calculations for a small sample of habitat bin 7 ponds. The corresponding PCA values that would be used in modeling are provided in

Table 12.

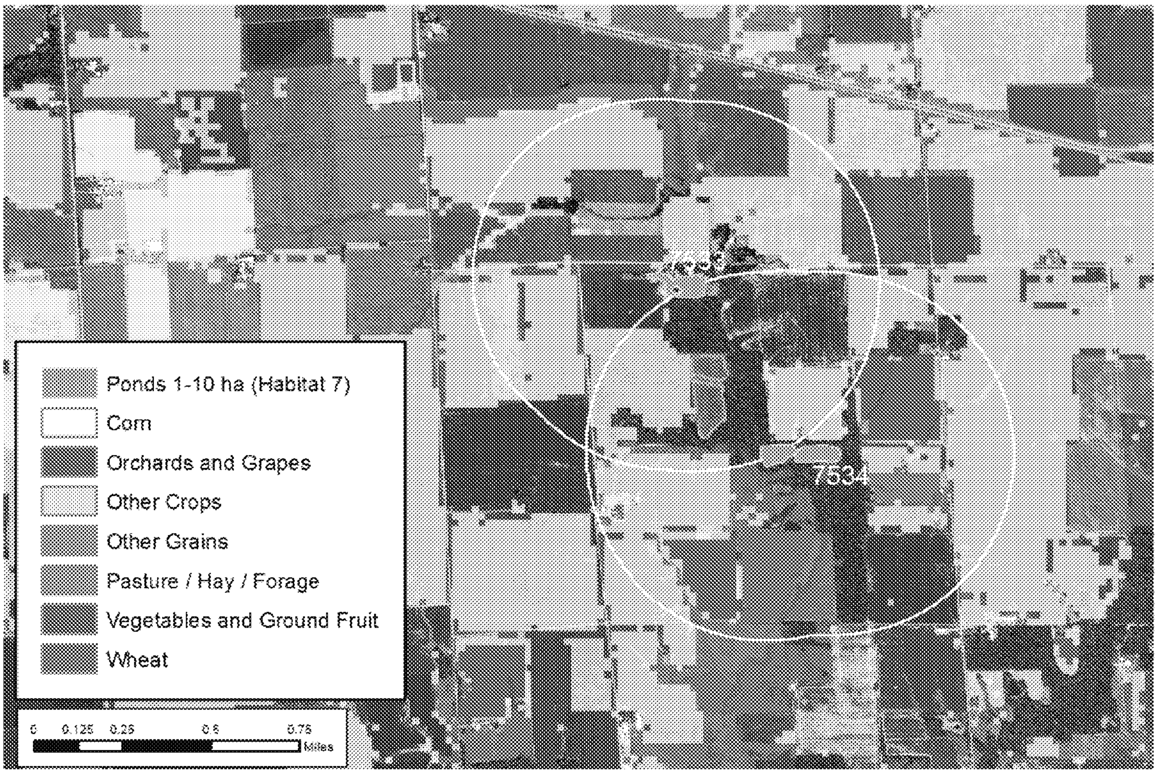

Figure 3. Crop PCA example.

Table 12. Table corresponding to figure above with Pond ID, Crop PCA.

Pond	Habitat Bin	Crop Group	PCA
7533	7	corn	46.3%

Pond	Habitat Bin	Crop Group	PCA
7533	7	pasture/hay/forage	2.5%
7533	7	wheat	0.1%
7534	7	corn	36.4%
7534	7	pasture/hay/forage	9.7%
7534	7	wheat	8.3%

2.2.6.2. Spray Drift Modeling

Concentration predictions may be very sensitive to spray drift deposition directly onto water bodies. Therefore, a realistic representation of drift based on a range of observed crop proximities to water is important. For habitat bins 6 and 7, water body-integrated drift fractions for each crop in a crop configuration was computed based on: spray drift-distance curves from the AGDISP version 8.26 (Bilanin et al., 1989; Teske and Curbishley, 2011), the distance from the waterbody to the nearest treated field, and the approximate length of the water body..

The method for developing the probability distributions of water body-integrated spray drift fractions for habitat bins 6 and 7 involved three computational steps:

1. Deriving drift-distance curves using the AGDISP model
2. Calculating the proximity of cropped areas to water body edges including a 25 feet setback for aerial applications
3. Calculating the water body-integrated drift fraction for all pools

In the first step, drift-distance curves were calculated for aerial applications of malathion to three different crop types using the AGDISP version 8.26 model with Tier III Aerial (Agricultural) option. Three aerial drift curves (row crops, orchards, and pasture) were developed using AGDISP to represent the range in crops receiving aerial applications. The differences in the input assumptions included the surface roughness of the crops and the tank mix of the spray material (Table 13). The tank mixes for all three drift curves required addition of a carrier to meet the minimum recommended spray volume of 5 gallons/acre. Example calculations of the tank mixes for these three drift curves are provided in

Table 14.

The drift curves are shown in Figure 4. The highest drift fraction is 0.379, 0.330, and 0.393 for row crop, orchard, and pasture, respectively. Note that the malathion non-ULV label has a 25 ft buffer, so the highest drift fraction is not applied. Overall, the row crop and pasture aerial drift curves are higher than orchard curve. This is expected since the orchards have higher surface roughness resulting from larger canopy coverage.

Table 13. Input parameters for aerial AGDISP drift curves.

Input Parameter	Value	Notes
Aircraft	Air Tractor AT-401	AGDISP/AgDRIFT Tier III Default
Nozzles	42 nozzles, 76.32% span	AgDRIFT Tier III Default
DSD	ASAE Medium	DV50 = 294.15; Label states use medium or coarser droplet size
Release Height	10 ft	Label

Flight lines	20	AgDRIFT Tier III Default
Swath Width	60 ft	AgDRIFT Tier III Default
Swath displacement fraction	22.33 ft	AgDRIFT Tier III value of 0.3722 swath displacement fraction
Swath offset	0	AgDRIFT Tier III Default
Wind Speed	10 mph	Label max
Wind Direction	-90	AGDISP/AgDRIFT Tier III Default
Temperature	86	AgDRIFT Default
Relative Humidity	50%	AGDISP/AgDRIFT Tier III Default
Stability	Overcast	AGDISP/AgDRIFT Tier III Default
Surface Roughness	Row Crop: 0.3937 ft	Midpoint of "Crops, depending on wind speed" (AgDRIFT Manual Table 5)
	Orchard: 2.46 ft	Midpoint of "Orchards, seasonal variations" (AgDRIFT Manual Table 5)
	Pasture: 0.1968 ft	Midpoint of "Grass 0.02 to 0.1 m high" (AgDRIFT Manual Table 5)
Specific Gravity (active plus additive)	1.067 g/mL	From Mal 57% MSDS
Tank Mix, Active Fraction (non-volatile fraction = 1.0)	Row Crop: 0.0518	1.) Malathion 57% label, 57.3% MAL, 95.45% additive; additive ingredients assumed to be non-volatile 2.) Contains 5 lbs active/gal 3.) 5 gal/acre minimum water volume 4.) Row crop single app. rate of 2.5 lb a.i./ac (cotton) 5.) Orchard single app. rate of 3 lb a.i./ac (peach) 6.) Pasture single app. rate of 1.25 lb a.i./ac (alfalfa)
	Orchard: 0.0271	
	Pasture: 0.0611	
Tank Mix, Additive Fraction (non-volatile fraction = 1.0)	Row Crop: 0.0391	
	Orchard: 0.0205	
	Pasture: 0.0461	
Tank Mix, Carrier Fraction	Row Crop: 0.9091	
	Orchard: 0.9524	
	Pasture: 0.8929	
Spray Volume rate (gal/acre)	Row Crop: 5.5	Carrier (water) rate plus MAL 57% rate
	Orchard: 5.25	
	Pasture: 5.60	

Notes:

1.) The tank mix fractions were adjusted slightly from original based on the minimum of 5 gallons of water as opposed to 5 gallons of tank mix

Table 14. AGDISP tank mix calculations example.

Crop	AI Rate (lb ai /acre)	Rate (gal/acre)	Carrier (Water) Rate (gal/acre)	Active fraction	Additive fraction	Tank Mix Active fraction	Tank Mix Additive fraction	Tank Carrier Fraction
Row Crops	2.5	0.500	5.000	0.57	0.43	0.0518	0.0391	0.9091
Orchard	3	0.600	5.000	0.57	0.43	0.0611	0.0461	0.8929
Pasture	1.25	0.250	5.000	0.57	0.43	0.0271	0.0205	0.9524

1. Label used: Cheminova Malathion 57% Organophosphate

2. Specific density: 1.067

3. Active content: 5 lb ai/gal

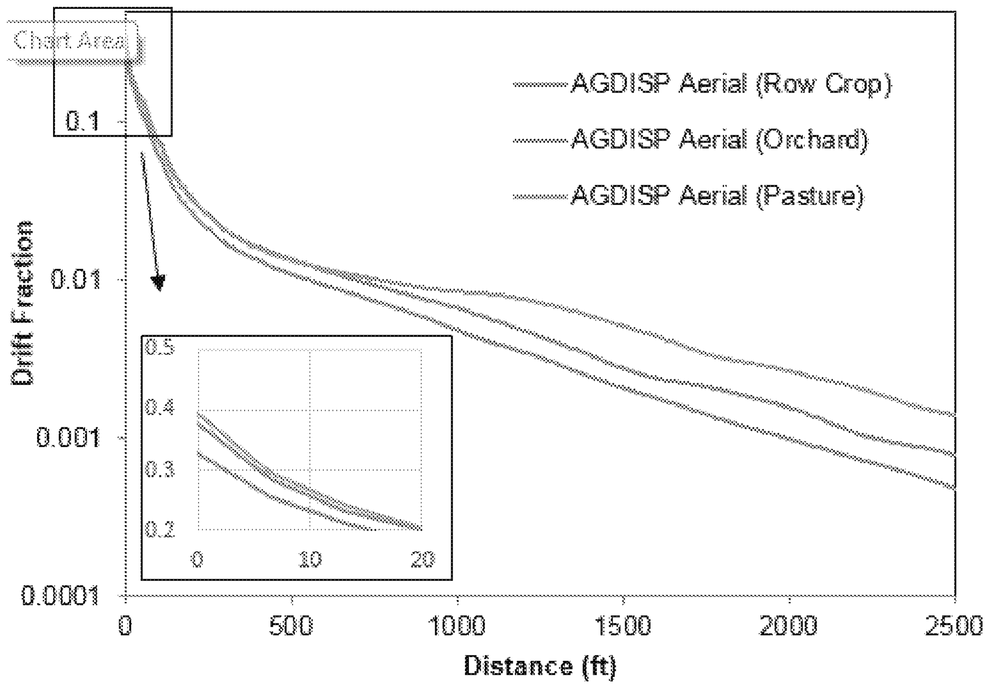

Figure 4. AGDISP aerial drift curves for malathion resulting from application on row crop, orchard, and pasture crop groups.

Next, for every pond in habitat bins 6 and 7, the distance from the pond edge to the nearest edge of each potentially treated crop was calculated to determine the application distance. These proximity distances were calculated using the Esri's ArcGIS "Near" tool, which determines the distances using vector representations of the pond and the crop areas, a more accurate method than raster based calculations. The Cheminova malathion 57% product label specifies restrictions on aerial application within 25 feet (7.62 m) of water. Therefore, spray drift was calculated for ponds closer than 25 ft to crop assuming that applications are made in compliance with the 25 feet restriction. Actual proximities were used to calculate drift for ponds greater than 25 feet from cropped areas. Using this approach, of the example ponds shown in (Figure 5), the minimum required setback would be simulated for corn and pasture while the actual pond-crop proximity would be simulated for wheat near pond ID 123832.

In the third and final step, water body-integrated drift fractions were derived by integrating the section of the drift curve that overlapped with the downwind pond length. Downwind pond length was calculated as the square root of the pond surface area (10 m, and 100 m for habitat bins 6, and 7, respectively). Ponds were conservatively assumed to always be downwind of the field. Drift curves were translated back from the pond edge according to the setbacks that were measured in step 2. A conceptual model of the water body-integrated drift fraction calculation is shown in Figure 6. The overall drift fraction for the pond was calculated as the integral of the drift curve divided by the pond length. Ponds more than 792 m from cropped areas (the distance as which drift becomes negligible) were assumed to have no spray drift exposure. The resulting drift fraction distributions for all habitat bin 6 and 7 ponds across all crops is shown in Figure 7. The larger bin 7 ponds had lower pond-integrated drift fractions (up to 5%) than the smaller bin 6 ponds (up to 15%)

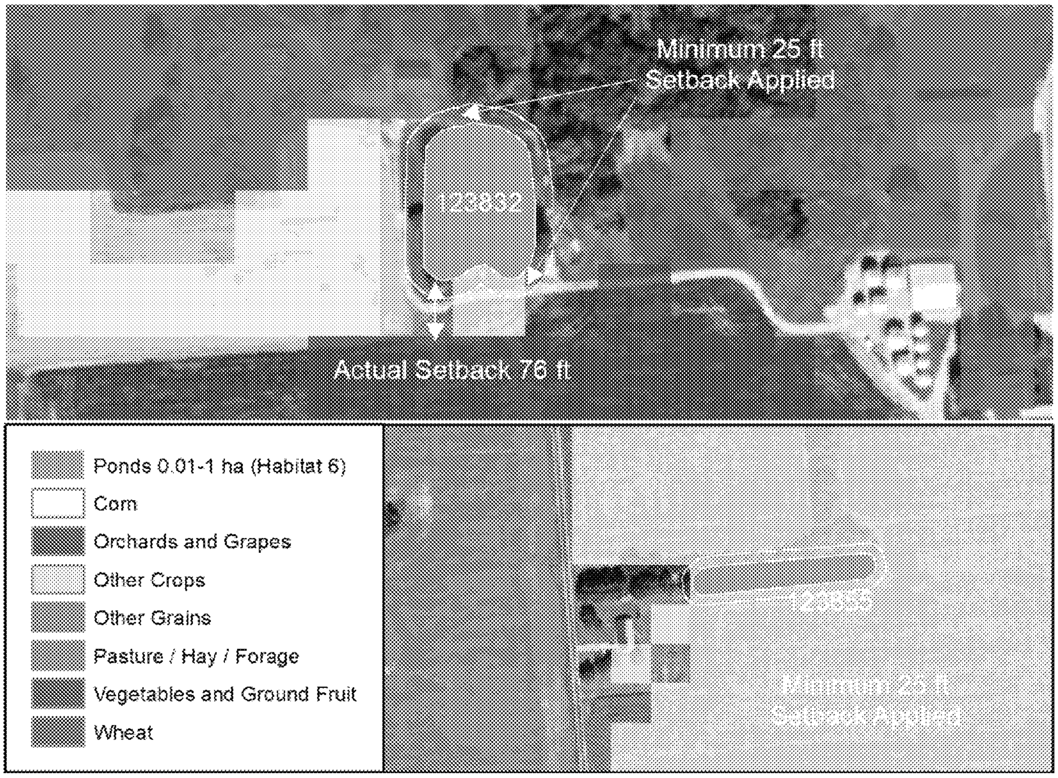

Figure 5. Conceptual example of spray drift distance calculations.

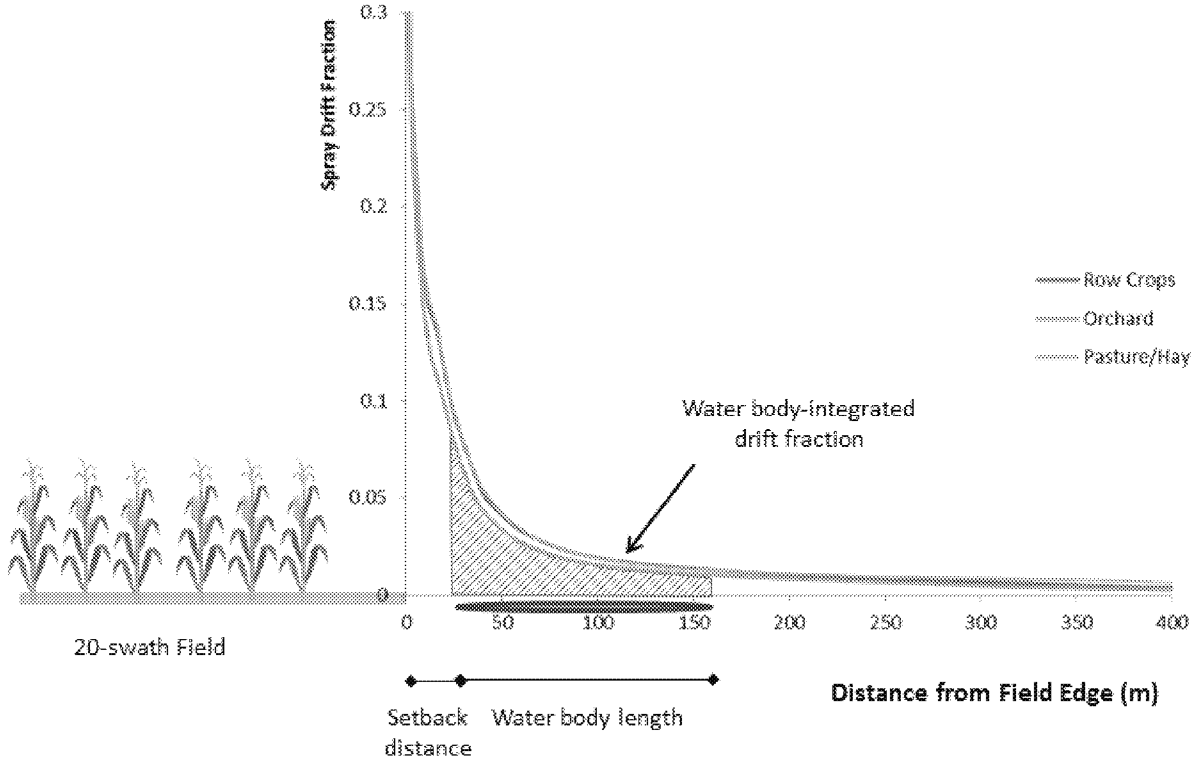

Figure 6. Conceptual model of water body-integrated drift fraction calculation.

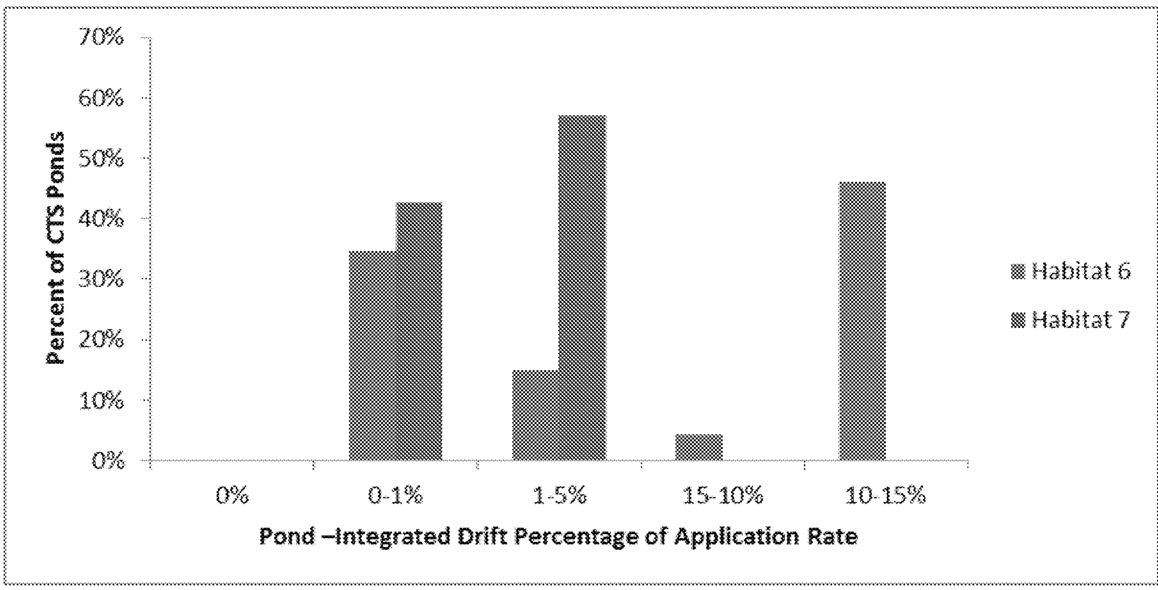

Figure 7. Distribution of percent drift for habitats 6 and 7.

2.2.7. Waterbody Characteristics

Surface area and depth assumptions were important for determining the volumes of potential malathion receiving waters. Given the same malathion loading, ponds with smaller volumes would result in higher exposure concentrations. The EPA and the Services provided definitions for each static water habitat bin that includes a range of water volumes associated with each (EPA, 2016a). These characteristics are shown in Table 15. For this initial demonstration of the Step 2 refined exposure modeling approach, the choice was made to assume constant water body sizes to represent each of the three aquatic bins. The most conservative, low end of the volume range was selected. Many of the species assessed are found in multiple habitat bins and the combined exposure distributions from those multiple bins provide variability in the water body volume assumptions. Incorporation of within-bin habitat volume ranges into the refined assessment can be readily implemented if assumptions on the likelihood of volumes across the range can be made.

Table 15. Static water body habitat bin characteristics.

Generic Habitat	Bin	Volume Range (m^3)	Modeled Volume (m^3)	Depth (m)	Width (m)	Length (m)
Medium Volume	6	100 - 20,000	100	1	10	10
High Volume	7	> 20,000	20,000	2	100	100

Other characteristics of the receiving water bodies modeled, such as concentration of suspended sediments, dissolved organic carbon, biomass, sediment bulk density, benthic porosity, and benthic depth were assumed to have VVWM default values used for the standard EPA farm pond.

2.2.8. Landscape Characteristics

The area of the agricultural field modeled in PRZM (the pond watershed) is an important feature defining the total mass of malathion applied to the field and the total malathion load in runoff and eroded sediment streams. Watershed areas for the static water body habitats were developed specifically for HUC 2 05 based on regional precipitation and evaporation data. An approximate water balance calculation estimated the watershed area required to generate enough annual runoff to offset evaporation from the pond. The method was similar to that followed by EPA in determining static water body areas in their BE (EPA, 2016a), but imposed constraints on the minimum and maximum watershed areas to fall within a targeted range equivalent to drainage area to normal capacity ratios (DA/NC) of between 5 and 15 m^2/m^3. This DA/NC ratio range is the same range of values that EPA targeted for the median DA/NC ratios across all the HUC2s in their BEs. An additional watershed characteristic that is dependent upon the watershed area is the hydraulic length. The hydraulic length affects the peak flow rate term in the calculation of erosion rates. This length was assumed to be the diameter of a circle with an area equal to the watershed area, a method consistent with EPA calculation of hydraulic length for static water bodies. The watershed characteristics for each of the habitat bins in HUC2 05 are shown in Table 16.

Table 16. Static water body habitat bin watershed characteristics.

Generic Habitat	Bin	Watershed Area (m^2)	DA/NC Ratio	Hydraulic Length (m)
Medium Volume	6	500	5	25.23
High Volume	7	100,000	5	356.82

Many components to the landscape characteristics (other than soils as previously discussed) are based on the representative PRZM scenario selected for each crop group. This includes crop emergence, maturity and harvest dates, crop root depth, canopy coverage, canopy interception storage of precipitation, crop practice factors, Manning's surface roughness coefficients, and irrigation method and rate, pan evaporation factor, minimum evaporation depth, and snow melt factor. These landscape characteristics were common for all simulations within a crop group and were not varied regionally or probabilistically. The representative PRZM scenarios assigned to each crop group were selected following three steps. The first step was to identify the scenario for each crop group within each HUC2 with the highest curve number to represent the crop group. Next, associations between crop groups that could serve as surrogates for other crop groups were made. For example, scenarios for wheat could represent the small grains crop group. Finally, if a scenario did not exist for a crop group or its surrogate crop group within HUC2 05, then a scenario from the closest neighboring HUC2 with an existing scenario for the crop group was chosen. A listing of the malathion crop groups modeled in HUC2 05 and their associated representative PRZM scenarios are provided in Table 17.

Table 17. Representative PRZM scenarios for malathion crop groups.

Malathion Crop Group	PRZM Scenario
Corn	OHCornSTD
Cotton	NCcottonSTD
Orchards and grapes	NCappleSTD
Other crops	ORgrassseedSTD
Other grains	KSsorghumSTD
Other row crops	NCpeanutSTD
Pasture/hay/forage	NCalfalfaOP
Wheat	KSsorghumSTD
Vegetables and ground fruit	ILbeansNMC

An important PRZM model input parameter that represents the runoff potential of the land cover and soil combination is the runoff curve number (CN). The CN values from the PRZM standard scenarios varied based on the hydrologic soil group (HSG) of the soil group sampled for a given PRZM simulation. Based on the HSG, the appropriate CN value for the crop group was selected from a lookup table. This lookup table was adopted from the crop group/HSG/curve number lookup table currently being used with EPA's development version of the Spatial Aquatic Model (EPA, 2015). This portion of this lookup that covers the malathion crop groups is presented in Table 18.

Table 18. Runoff curve number for malathion crop groups in HUC2 05.

Crop Group	Soil Hydrologic Group							
	A		B		C		D	
	Crop	Fallow	Crop	Fallow	Crop	Fallow	Crop	Fallow
Corn	64	74	74	83	81	88	85	90
Cotton	64	74	74	83	81	88	85	90

Orchards and grapes	57	57	73	73	82	82	86	86
Other crops	64	74	74	83	81	88	85	90
Other grains	60	74	72	83	80	88	83	90
Other row crops	64	74	74	83	81	88	85	90
Pasture/hay/forage	49	49	69	69	79	79	84	84
Vegetables and ground fruit	64	74	74	83	81	88	85	90
Wheat	60	74	72	83	80	88	83	90

2.2.9. Percent Treated Area

The percent of eligible crop areas actually treated with malathion is important to characterizing actual exposure probabilities to the species. Percent treated areas (PTA) were calculated for each crop in the Ohio River Basin region and combined through weighted-averages to achieve an estimate of PTA across all crops for each species. The PTA was factored in to the exposure distributions in post-processing modeling results. Since any untreated crop area would have zero exposure, the probability weights in the distribution can be scaled by the percent of crop area not treated (1-PTA). This effectively accounts for including EECs in the distribution with values of 0 proportional to the untreated crop in the species range.

A variety of sources, such a personal communications with extension agent and university professors, indicated that not all of the labeled crops in the HUC2 05 region may be treated with malathion. This was further confirmed with quantitative data in the AgroTrak (GfK Kynetec, 2015) pesticide use database. The AgroTrak data from years 2006 and 2013 was used to calculate the percent treated area (PTA) by state, crop group, and year. The data contains information about crop acres grown and base acres treated. Crop acres grown and base acres treated were totaled for each state, crop group, and year. The percent treated area was then calculated by dividing the base acres treated by the total crop acres grown. With a PTA for each state, crop group, and year for 2006-2013, the final PTA for each state and crop group was calculated as the 90% confidence interval on the mean PTA of 2006-2013 using the student's T-test:

$[PTA_{90}] = [MeanPTA] + (([t\text{-}value]*[StdDevPTA])/([\#Years]^{\wedge}0.5)))$

The number of years of data available determined the student t-value applied. This followed the same methodology as the EPA uses in calculating t90 half-life values. Crops in the Gfk database were associated to the crop groups being modeled. National data was used for other grains and wheat because state level data was not available. Sorghum was chosen to represent "other grains" since this crop group did not have Malathion data in the GfK database. The "other crops" crop group was represented with the highest PTA of all other groups by state since this group was also not in the GfK database. Results from the PTA analysis are shown in Table 19. Corn had some of the lowest PTA of 0.04% in most states while vegetables and ground fruit crop group had the highest PTA of 42.71% and 21.77% in Ohio and Pennsylvania, respectively.

Table 19. Percent treated area estimated for each state and crop group in HUC2 05 using the AgroTrak data from 2006-2013.

State	Corn	Cotton	Orchards and Grapes	Other crops**	Other grains*	Pasture/Hay/ Forage	Vegetables and ground fruit	Wheat*

Illinois	0.00%	0.45%	0.80%	0.80%	0.12%	0.60%	0.03%	0.25%
Indiana	0.04%	0.45%	0.99%	3.57%	0.12%	1.38%	3.57%	0.25%
Kentucky	0.04%	0.45%	0.99%	3.35%	0.12%	3.35%	3.48%	0.25%
Maryland	0.90%	0.45%	0.99%	0.90%	0.12%	0.93%	0.00%	0.25%
New York	0.00%	0.45%	0.53%	5.20%	0.12%	0.93%	5.20%	0.25%
North Carolina	0.04%	0.45%	0.00%	0.37%	0.12%	0.93%	0.37%	0.25%
Ohio	0.00%	0.45%	18.52%	42.71%	0.12%	0.04%	42.71%	0.25%
Pennsylvania	0.00%	0.45%	0.00%	21.77%	0.12%	0.00%	21.77%	0.25%
Tennessee	0.04%	0.75%	0.99%	7.08%	0.12%	0.93%	7.08%	0.25%
Virginia	0.04%	0.45%	0.00%	0.00%	0.12%	0.93%	0.00%	0.25%
West Virginia	0.04%	0.45%	0.00%	0.00%	0.12%	0.93%	3.48%	0.25%

*Indicates national averages were used to substitute for missing state data

**Maximum PTA of the other crop croups was used to substitute lack of data for the "other crops" group

Next, percent treated area was aggregated up to the species level. The malathion treated area in HUC2 05 was combined with catchments and state boundaries to determine the area of each crop group by state and catchment. Species were then associated with their catchments to calculate the total acres of species by state and crop group. To determine the fraction of area represented by each species in a state and crop group, the area was divided by the total area in HUC2 05 represented by the species. To determine the final weighted percent treated area by state, the species/state/crop fraction was multiplied by the state/crop group PTA established above and summed by species. The results of this analysis are summarized below in Table 20. Overall, the Kentucky cave shrimp has the highest PTA with 2.29% of its habitat overlapping malathion treated crops. The Rayed bean has the lowest weighted PTA at 0.49%.

Table 20. Weighted percent treated area (PTA) for each species.

Species Common Name	Species Scientific Name	Weighted PTA
Kentucky cave shrimp	Palaemonias ganteri	2.29%
Northern riffleshell	Epioblasma torulosa rangiana	1.11%

Madison Cave isopod	Antrolana lira	0.93%
Green blossom (pearlymussel)	Epioblasma torulosa gubernaculum	0.91%
Snuffbox mussel	Epioblasma triquetra	0.67%
Rayed bean	Villosa fabalis	0.49%

2.3. Model Simulation and Analysis

The model input parameters described in Section 2.2 were compiled into PRZM and VVWM input files for model simulation.

The model parameters or groups of model parameters with probabilistic representations of their variability in the environment were sampled according to their probability distributions. These parameters/parameter groups were: initial application date, weather station, soil profile and land surface slope, and crop configuration (consisting of spray drift fractions and PCA patterns), which account for the observed variations in possible pond-crop configurations and pathways of exposure. Unique combinations of values, for use in model input files, were drawn from these distributions using Sandia National Laboratory's Latin Hypercube Sampling (LHS) program (Swiler and Wyss 2004). Latin Hypercube sampling is designed to ensure that distributions are sampled from evenly-spaced percentile-ranges regardless of the number of samples. LHS ensures good coverage of the joint probability distribution with fewer samples than required using purely Monte Carlo sampling. LHS sampling was conducted to build multiple ensembles of 1000 unique input parameter sets based on the assumptions of the different modeling stages.

For a given input parameter sample, one PRZM simulation was conducted for each crop in the selected crop configuration. Soil and weather inputs were the same across PRZM simulations for the sample. Application dates were adjusted for each crop in the selected configuration.

The PRZM and VVWM models were simulated in series for each parameter set. Inputs required for each PRZM simulation included a custom PRZM input file containing pesticide, soil, crop, and application parameters and a SAMSON weather data file. Inputs required for the subsequent VVWM simulation included the PCA-weighted time series loading output from the corresponding PRZM simulations, the SAMSON weather data file, and a file of pesticide properties, water body characteristics, and PCA-weighted spray drift time series. Scripts were developed using Python to create and manage model input files and batch run the thousands of simulations.

EECs from all simulations were calculated for daily and 21-day average periods. Custom code was developed using Python scripts to calculate annual maximum daily average EECs for each simulation year from daily data (since this was not part of the default VVWM summary output). All of the EECs from each ensemble of 1000 30-year realizations were compiled into probability distributions for each species and are presented in Section 3.1.

3. RESULTS AND DISCUSSION

3.1. Exposure Modeling Results

Malathion annual maximum 1-day and 21-day exposure distributions were generated for each species based on a conservative assumption of 100% PTA for every malathion labeled crop, and based on actual PTAs calculated from best available data sources. For species that occurred in multiple aquatic habitat bins, EEC distributions were developed independently for each bin, and were also combined for species that occupied both Bin 6 and Bin 7 habitats. EEC distributions based on the conservative 100% PTA assumption are presented first followed by a final discussion of the PTA refinement.

3.1.1. Exposure Predictions Assuming 100% PTA

Each EEC distribution (one per species and habitat bin) consisted of 30,000 annual maximum values. Conservative distributions of EECs assuming 100% PTAs were generated considering potential exposure to all ponds within a species habitat range, including ponds that had no potential malathion use sites within their representative watersheds. These results are presented in Table 21.The 90th percentile annual maximum EECs range from a high of 0.392 ug/L for the Kentucky cave shrimp in Bin 6 habitat, to a low of 0.100 ug/L for the rayed bean in habitat Bin 7. This shows the variability of exposure likelihood across these different species habitat ranges. The median annual maximum EECs are generally 10 to 30 times lower than the 90th percentile annual maximum EECs. It should be noted that the EECs in the “Max” column represent the highest of 30,000 annual maximum values and would have a 0.003% probability of occurring.

Two species, the Kentucky cave shrimp and the Madison cave isopod, inhabit both Bin 6 and Bin 7. For the Kentucky cave shrimp, EECs in Bin 7 are almost 50% lower than Bin 6 EECs. For the Madison cave isopod, the 90th percentile EECs are similar between Bin 6 and Bin 7, however the maximum EEC is nearly double for Bin 6. The “All Habitat” EECs for these two species consider both the medium and large volume habitat together. Annual maximum 21-day EECs for the same species and habitat bins are shown in Table 22. The 21-day EECs are close to a factor of 10 lower than the annual maximum 1-day EECs.

Table 21. Annual Maximum 1-day EECs by species, Bin 6 and Bin 7 habitat.

Species Common Name	Bin 6 Annual Maximum 1-Day EECs (ug/L)				Bin 7 Annual Maximum 1-Day EECs (ug/L)				All Habitat Annual Maximum 1-Day EECs (ug/L)			
	Min	Median	90th -%ile	Max	Min	Median	90th-ile	Max	Min	Median	90th-ile	Max
Green blossom (pearlymussel)	-	-	-	-	0	0.007	0.207	6.99	-	-	-	-
Kentucky cave shrimp	0	0.033	0.392	16.72	0	0.023	0.279	7.19	0	0.027	0.332	16.7
Madison Cave isopod	0	0.008	0.179	15.69	0	0.008	0.178	8.00	0	0.008	0.179	15.7
Northern riffleshell	-	-	-	-	0	0.009	0.124	9.94	-	-	-	-
Rayed bean	-	-	-	-	0	0.009	0.100	11.09	-	-	-	-
Snuffbox mussel	-	-	-	-	0	0.009	0.112	4.41	-	-	-	-

1. EEC distributions include all exposed and non-exposed water bodies within the range of each species.

2. All Habitat EECs are derived from the combined distribution of annual maximum EECs from both Bin 6 and Bin 7 simulations.

3. The "Max" annual maximum is the highest out of 30,000 values, and has an 0.003% probability of occurring

Table 22. Annual Maximum 21-day EECs by species, Bin 6 and Bin 7 habitat.

Species Common Name	Bin 6 Annual Maximum 21-day EECs (ug/L)				Bin 7 Annual Maximum 21-day EECs (ug/L)				All Habitat Annual Maximum 21-day EECs (ug/L)			
	Min	Median	90th -%ile	Max	Min	Median	90th -%ile	Max	Min	Median	90th -%ile	Max
Green blossom (pearlymussel)	-	-	-	-	0	0.001	0.040	1.51	-	-	-	-
Kentucky cave shrimp	0	0.006	0.068	6.71	0	0.004	0.050	1.68	0	0.005	0.059	6.71
Madison Cave isopod	0	0.002	0.035	6.50	0	0.003	0.044	1.68	0	0.002	0.039	6.50
Northern riffleshell	-	-	-	-	0	0.002	0.024	1.95	-	-	-	-
Rayed bean	-	-	-	-	0	0.002	0.020	1.80	-	-	-	-
Snuffbox mussel	-	-	-	-	0	0.002	0.023	1.1	-	-	-	-

1. EEC distributions include all exposed and non-exposed water bodies within the range of each species.
2. All Habitat EECs are derived from the combined distribution of annual maximum EECs from both Bin 6 and Bin 7 simulations.
3. The "Max" annual maximum is the highest out of 30,000 values, and has an 0.003% probability of occurring

3.1.2. Exposure Predictions Including PTA Refinement

A detailed discussion on the analysis of best available malathion use data in the calculation of conservative species range specific PTA was provided in Section 2.2.9. The analysis showed that the uncommon use of malathion on the dominant crops occurring within these species ranges (corn and pasture) resulted in low PTAs for all species ranges of between 0.49% and 2.29%. To adjust the EEC distributions to reflect these PTAs, the annual maximum EEC distributions were shifted such that potential for exposure only occurred in the fraction of aquatic habitat within a species range equal to the PTA. The remaining fraction of aquatic habitat within the range did not co-occur with treated crops, and therefore had no exposure to malathion. Accounting for the PTA in the exposure distributions resulted in 90th percentile annual maximum 1-day and 21-day average EECs of 0 μg/L. In other words, given the low area of malathion treated crops (less than 3% for all species), the likelihood of any malathion exposure in any of the species ranges is less than 3%. A summary of the probability of exceeding a reference annual maximum 1-day concentration of 0.01 μg/L is is presented in Table 23 for each species and aquatic habitat bin.

Table 23. Probabilities of Annual Maximum 1-day concentrations exceeding the acute effects end point of the most sensitive species (0.122 μg/L).

	Probability of Annual Maximum 1-Day EEC Exceeding 0.01 ug/L	
Species Common Name	**Bin 6**	**Bin 7**
Green blossom (pearlymussel)	-	0.53%
Kentucky cave shrimp	0.89%	1.45%
Madison Cave isopod	0.25%	0.51%
Northern riffleshell	-	0.56%
Rayed bean	-	0.25%
Snuffbox mussel	-	0.34%

All probabilities shown are reflect the species range specific PTA

3.2. Comparison with EPA Assessment

The probabilistic exposure modeling approach presented in this report was designed as an alternative to the EPA BE approach to Step 2 aquatic exposure modeling. A comparison of the species specific refined annual maximum 1-day EECs from this assessment to EPA's Step 2 EECs (EPA, 2016a) is presented in Table 24.The conservative EECs from this Step 2 assessment (which assume 100% PTA) are more than 2 orders of magnitude lower than EPA's Step 2 estimates for Bin 6 and Bin 7. The more refined, and more realistic, EECs based on the PTA refinement reflect the very low likelihood of malathion exposure in the aquatic habitats of the six species assessed. The limited use of malathion on corn and pasture in the HUC2 05 region is one of the primary factors leading to 99th percentile annual maximum EECs of 0 for four out of the six species ranges assessed. Additional scenarios reflecting hypothetical estimates of future PTA could readily be incorporated into this analysis to further understand the impacts of malathion use extent and frequency on the likelihood malathion affecting endangered species.

Table 24. Comparison of Step 2 refined annual maximum 1-day EECs with EPA Step 2 EECs for malathion.

	EPA Step 2, 93rd %-ile[1] (ug/L)		FMC Step 2, 90th %-ile, 100% PTA (ug/L)		FMC Step 2, PTA Refinement[2] (ug/L)		
Species Common Name	**Bin 6**	**Bin 7**	**Bin 6**	**Bin 7**	**90th %-ile**	**99th %-ile**	**99.9th %-ile**
Green blossom (pearlymussel)	163	28	-	0.280	0.0	0	0.25
Kentucky cave shrimp	163	28	0.396	0.283	0.0	0.044	0.98
Madison Cave isopod	163	28	0.209	0.209	0.0	0	0.19
Northern riffleshell	163	28	-	0.130	0.0	8.2E-05	0.14
Rayed bean	163	28	-	0.107	0.0	0	0.05
Snuffbox mussel	163	28	-	0.120	0.0	0	0.08

1. EPA's Step 2 EECs were annual maximum peak (not 1-day) 1-in-15 year EECs within HUC2 05.

2. Based on the habitat bin with the highest EECs for the species.

3.3. Comparison with Monitoring Data

Monitoring data in HUC2 05 was retrieved to provide additional context to the modeling results generated in this study. The monitoring data from non-targeted studies presented below is not appropriate for use in calibration or validation of model results, rather it is provided for qualitative discussion. Monitoring data provides an indication of the presence and background levels of pesticide concentrations in a variety of networked flowing water bodies. Comparison of the monitoring data to modeled concentrations in smaller unconnected static water bodies serves to test the hypothesis that detections occur more frequently and at lower concentrations in flowing waters than static waters.

Surface water monitoring data was obtained for malathion from the Water Quality Portal (http://www.waterqualitydata.us/). This portal is a cooperative service between the USGS, the US EPA and the National Water Quality Monitoring Council and integrates publicly available data. Data were selected using the location filter for HUC2 05 and the chemical name malathion. An initial set of 7,646 records was downloaded. These results were further filtered using the following criteria:

- Date >= 1990
- Type = "Sample – routine" (no QC samples)
- Sample Fraction Test = "Dissolved"
- Media = "Surface water"
- Result status = "Accepted" or "Historical" (preliminary were excluded)

After applying the filters above, 2,130 results were available for analysis. Results are summarized by year in <cross reference here>. Detections occurred in 2.5% of the 2,130 results with the 90th percentile value over all years equal to 0.08 ug/L. The highest concentration of 0.21 ug/L occurred in 2004. The highest percent of detections occurred in 1994 (57%), 1995 (17%), and 2002 (10%). There were no detections in this watershed from 2006 – 2012.

Table 25. Malathion monitoring data by year for HUC2 05 watershed from NAWQA database.

Year	Count of Results	Count Non Detects	Count Detections	Mimimum (ug/L)	Maximum (ug/L)
1992	10	10	0		
1993	10	10	0		
1994	7	3	4	0.017	0.050
1995	12	10	2	0.003	0.010
1996	24	22	2	0.012	0.020
1997	131	128	3	0.005	0.130
1998	109	106	3	0.008	0.020
1999	165	164	1	0.026	0.030
2000	196	185	11	0.004	0.120
2001	118	114	4	0.003	0.020
2002	125	112	13	0.003	0.100
2003	150	145	5	0.002	0.010
2004	164	161	3	0.01	0.210
2005	118	117	1	0.008	0.010

2006	67	67	0		
2007	68	68	0		
2008	60	60	0		
2009	65	65	0		
2010	57	57	0		
2011	71	71	0		
2012	67	67	0		
2013	336	334	2	0.0041	0.0286
All years	2,130	2,076	54	0.002	0.210

In comparison to monitoring data, the modeled concentrations could be several orders of magnitude greater than the maximum monitoring concentration but with low likelihood of occurrence. In contrast, monitoring data show a higher frequency of low concentrations. This finding is consistent with the conceptual model that the flowing water bodies (typically sampled in monitoring programs) have lower concentrations than their static counterparts. The higher frequency of monitoring detections is consistent with the generally much larger drainage areas of flowing waterbodies. The smaller watersheds of the static waterbodies resulted in concentrations that were more sensitive to localized crop proximity. Significant crop in a static pond watershed may result in elevated concentrations. However with low overall cropped and treated area in the species ranges, the frequency of elevated concentrations was low.

3.4. Conservative Assumptions and Uncertainty

This assessment has been developed with the best available data concerning crop and land cover, soils, malathion use and application practices. Many of the uncertainties and deficiencies in EPA's Step 2 analysis, which considered only one model simulation per malathion use in HUC2 05, have been quantitatively addressed in this refined aquatic exposure assessment. These sources of uncertainty include:

- Malathion application timing: Uncertainty in application timing was accounted for by determining a window based on regional agronomic practices and randomly drawing a potential application date from within that window.
- Soil and slope conditions within species range: Probability distributions of combinations of soil and slope conditions occurring within a given species habitat were allowed for the actual variability of soils specific to a given species range to be simulated.
- Weather conditions within species range: All weather stations that were located near or within a given species range were sampled in generating exposure simulations.
- Spray drift contributions to exposure based on crop proximity to water bodies: Proximity distances were calculated from every pond to every malathion crop group to determine the appropriate pond-integrated spray drift fraction for malathion applications to a given crop in a each pond watershed.
- Percent Cropped Area (PCA): A rigorous assessment of PCA was conducted by constructing probability distributions of crop configurations (combination of crops) surrounding individual ponds within species range. This allowed for the combined effects of multiple crops in a pond watershed to be assessed using crop specific PCAs to accurately represent the contributions of each crop to pond EECs.
- Percent Treated Area (PTA): PTA was conservatively accounted for based on best available, regionally specific malathion use data.

- Species relevance: EEC distributions were generated specific to each species range assessed and for each aquatic habitat bin the species occupies. This addressed the uncertainty in EPA modeling that assigned the same EECs to all species within a given HUC2, regardless of the location of that species range relative to cropping patterns.

Quantitatively accounting for the sources of uncertainty listed above resulted in a robust, species and habitat specific probability distribution of EECs.

While this assessment addressed many uncertainties unaccounted for in the EPA BE approach, there are several additional known sources of uncertainty that remain in this analysis and may be addressed in future work for continuing improvement of the scientific methods. These include the following:

- Pond volume/surface area: The minimum volumes and surface areas for each habitat bin were assumed in all simulations. This resulted in a very conservative assumption from the standpoint of spray drift potential. With better depth and volume variability information, uncertainty in concentration predictions could be refined further.
- Pond watershed area: The pond watershed areas in this assessment represent DA/NC ratios that have historically been considered conservative in ecological aquatic exposure risk assessments (i.e., the same DA/NC ratios as the EPA standard farm pond). In reality, pond watershed areas will vary across the landscape and could have an impact on potential exposure.
- Pond hydrology. This assessment assumed that ponds maintain a constant volume and do not over flow during large runoff events. For water bodies in the relatively humid eastern United States, pond overflow is likely during large storm events. The assumption of constant volume and no overflow is a source of conservatism in this assessment.
- Crop configurations: The crop configurations for each pond were based on crop group classifications representing the dominant crop out of 5 years of CDL. From year to year, crop configurations (fractions of pond watersheds in different crop groups) will vary. The dominant crop configuration will contain a malathion treated area that is higher than some years and lower than other year. Alternative approaches to the dominant approach would be to generate multiple crop configurations for each pond based on each year of CDL data. While this approach would broaden the population of crop configurations to simulate and also broaden the resulting EEC distribution, the effects on the 90th percentile exposure probability is likely to be small.
- Spray drift contributions to exposure: The effects of wind speed and wind direction on spray drift contributions to exposure were not accounted for. The assumption of a 10 mph wind speed always blowing in the direction from the treated field to the receiving water was held constant for all simulations.
- Spray drift buffer effects on runoff: Runoff was modeled with direct entrance to the receiving waters without attenuation through buffers, resulting in exposure estimates biased high. Although a vegetated buffer is not required on MAL labels, buffers are a best management practice encouraged by the Natural Resources Conservation Service (NRCS) to mitigate not only pesticide losses but nutrients as well (USDA, 2000). In addition, the effects of vegetation and riparian buffers as wind breaks, is not accounted for in the spray drift modeling. However, vegetation intercepts spray drift prior to its entry into a receiving water body, thus reducing the potential for aquatic exposure (Porskamp et al. 1994; Zande et al. 2000). Concentration predictions based on modeling the effects of vegetative buffers would be lower and more realistic.
- Number of simulations in the ensemble - Each distribution of annual maximum concentrations was composed of 1000 simulations for a total of 30,000 annual maximums. Sampling four random

variables with a full factorial combination of each decile of their distributions would require 10^4 unique input parameter sets and simulations. In future work, a convergence analysis will be conducted to ensure this ensemble size provides sufficient accuracy in reasonable computation time, however previous work suggests 1000 simulations is appropriate.

- Percent Treated Area (PTA): The PTAs for each crop were based upon the upper 90th percentile confidence interval on the sample mean from eight years of use data (2006-2013) from the AgroTrak database (Pai et al., 2016). As has been shown, the PTAs estimated for MAL were very low, and zero in some states. Corn, in particular had very low PTA's of less than 1% or zero. The PTAs on pasture/hay, the most dominant malathion crop within the ranges of the species assessed, were as high as 3.35% in Kentucky. The resulting PTAs for each species habitat ranged from a low of 0.49% for the rayed bean to 2.29% for the Kentucky cave shrimp. These low PTA values realistically reflect the limited use of malathion on crops in this region. Very similar malathion use data was presented in Appendix 1-8 of the malathion BE (EPA, 2016a). This analysis evaluated malathion use between 2008 and 2012 (a shorter time period than was evaluated in this assessment), and also showed that malathion usage on corn was close to 0%, with the only reported use occurring in Minnesota. The malathion use analysis in the BE showed use on alfalfa to be approximately 1%, with the highest use in AR, CA, SD, NV, and WY, all states outside of HUC2 05.

4. CONCLUSIONS

This study demonstrated a refined malathion aquatic exposure modeling approach applied to species inhabiting static water habitats in the Ohio River basin, HUC2 05. The assessment evaluated all endangered crustaceans, mollusks, and fish that may inhabit water bodies with EPA habitat bin 6 and 7 characteristics. This study was motivated by the recognized need to develop approaches that quantitatively account for uncertainty in environmental and agronomic factors that impact the potential effects of pesticide use on endangered species. The approach presented in this study was designed to fit within Step 2 of the endangered species effects determination process when decisions of "likely to adversely affect" or "not likely to adversely affect" are made.

The refined Step 2 aquatic exposure modeling approach differed significantly from the Step 2 aquatic exposure modeling approach presented in EPA's malathion BE (EPA, 2016a), and followed many of the NAS panel recommendations on approaches for estimating risks to endangered species from pesticides (NRC, 2013). The most significant differences between the Step 2 modeling approach demonstrated in this assessment and EPA's Step 2 approach can be categorized as follows:

- Species exposure relevance: The exposure predictions generated in this assessment were specific to individual species ranges based on the best available species location data. The exposure predictions in EPA's Step 2 analysis were at the HUC2 scale.
- Use of best available spatial data: This assessment used best available crop, soils, and hydrography spatial datasets to characterize the critical exposure-influencing landscape conditions surrounding static water body habitat within species ranges. EPA's assessment used a single representation of landscape conditions per crop group to represent all species habitat within a HUC2 region.
- Agronomic practices: Variability in malathion application timing following regionally specific practices was accounted for in this assessment to achieve a more realistic estimate of resulting exposure. The approach followed by EPA considered only a single application per crop group and HUC2.
- Pesticide use: This assessment included a refinement of the percent treated area based on eight years of recent malathion use data. The EPA's assessment assumed 100% treated area for all crops.
- Probabilistic analysis: The exposure modeling approach used in this assessment incorporated probability distributions of application timing, weather, soil and slope conditions, and crop configurations around ponds to generate 1,000 30-year pond realizations per species, with each realization comprised of 1 to 5 PRZM simulations. EPA's Step 2 modeling for malathion considered just 1 or 2 PRZM/VVWM simulations per crop group within a HUC 2.

The spatially explicit, probabilistic aquatic exposure modeling approach followed in this study resulted in refined EECs that for many species were two to three orders of magnitude lower than the EPA Step 2 analysis suggested for species occurring in the medium (Bin 6) and high volume (Bin 7) habitats. These conservative EECs were based on the assumption of 100% PTA for labeled malathion crops. Analysis of historical malathion use data from both EPA (EPA, 2016a) and as part of this study has shown malathion use to cover less than 1% of the dominant crops in the HUC2 05 region. Accounting for actual PTA resulted in more realistic EECs. The probabilities of maximum 1-day malathion exposure concentrations exceeding a reference concentration (0.01 μg/L) were determined to be between 0.25% and 1.5% depending upon species and habitat characteristics. This methodology is readily reproducible and extendable to assess aquatic species in the remaining HUC2 watersheds across the United States and will continually be improved as better data and computational methods become available. The approach presented in this study was demonstrated within Step 2 of the endangered species effects determination process, but can be applied both in earlier and later steps.

The results of this pilot project are preliminary due to the short timeframe given to us to review and respond to the Agency draft BEs. As such. we do not currently support these analyses as a predicate for regulatory action for malathion. We continue to evaluate and refine this approach and intend to provide our final analyses as part of a refined national endangered species assessment that is currently under development.

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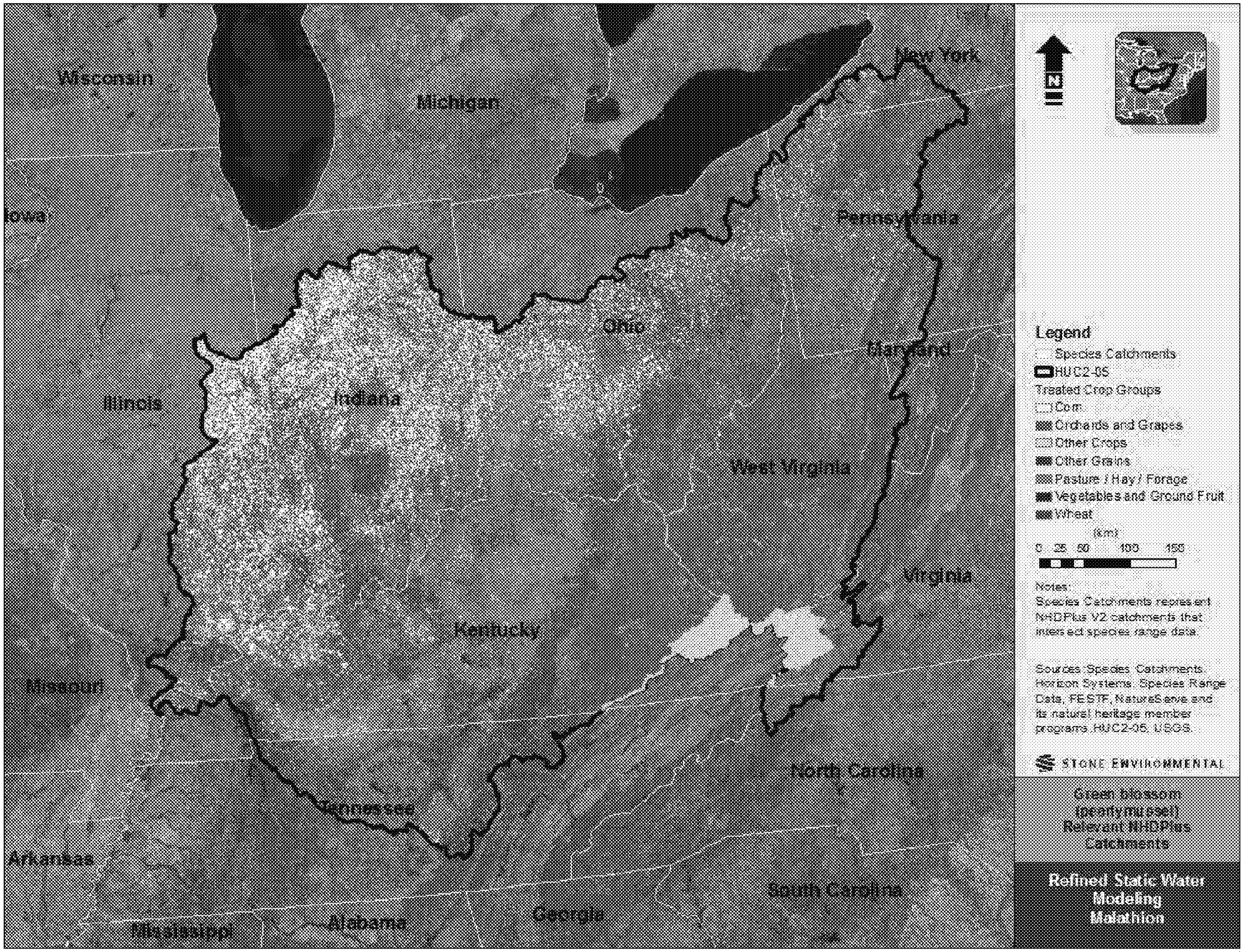
APPENDICES

APPENDIX A



Wisconsin
Michigan
New York
Iowa
Pennsylvania
Ohio
Maryland
Illinois
Indiana
West Virginia
Virginia
Kentucky
Missouri
North Carolina
Tennessee
Arkansas
South Carolina
Georgia
Alabama
Mississippi
N
Legend
Species Catchments
HUC2-05
Treated Crop Groups
Corn
Orchards and Grapes
Other Crops
Other Grains
Pasture / Hay / Forage
Vegetables and Ground Fruit
Wheat
(km)
0 25 50 100 150
Notes:
Species Catchments represent NHDPlus V2 catchments that intersect species range data.
Sources: Species Catchments, Horizon Systems. Species Range Data, FESTF, NatureServe and its natural heritage member programs. HUC2-05, USGS.
STONE ENVIRONMENTAL
Green blossom (pearlymussel) Relevant NHDPlus Catchments
Refined Static Water Modeling Malathion

Figure 8. Green blossom species catchments in HUC2 05.

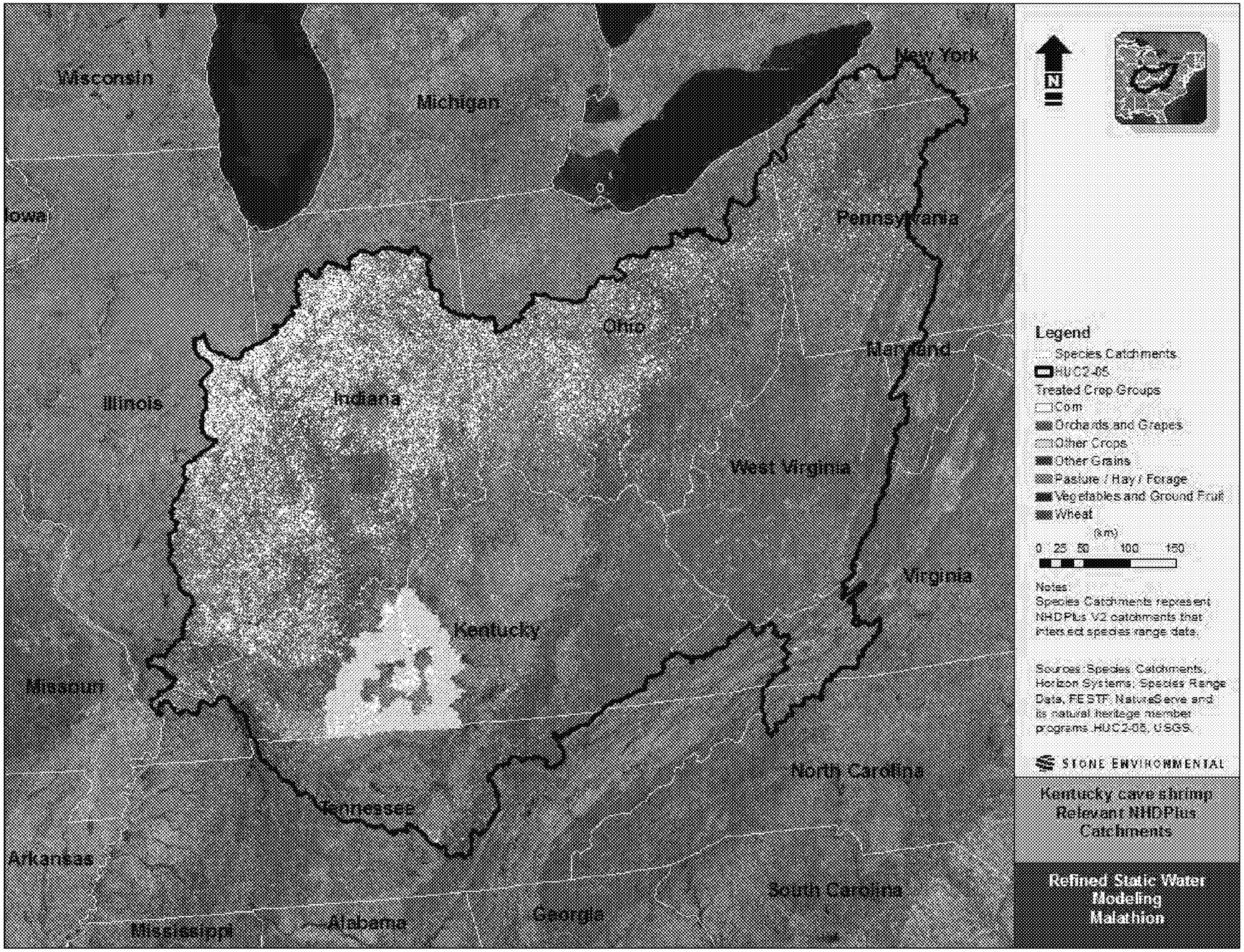


Figure 9. Kentucky cave shrimp species catchments in HUC2 05.

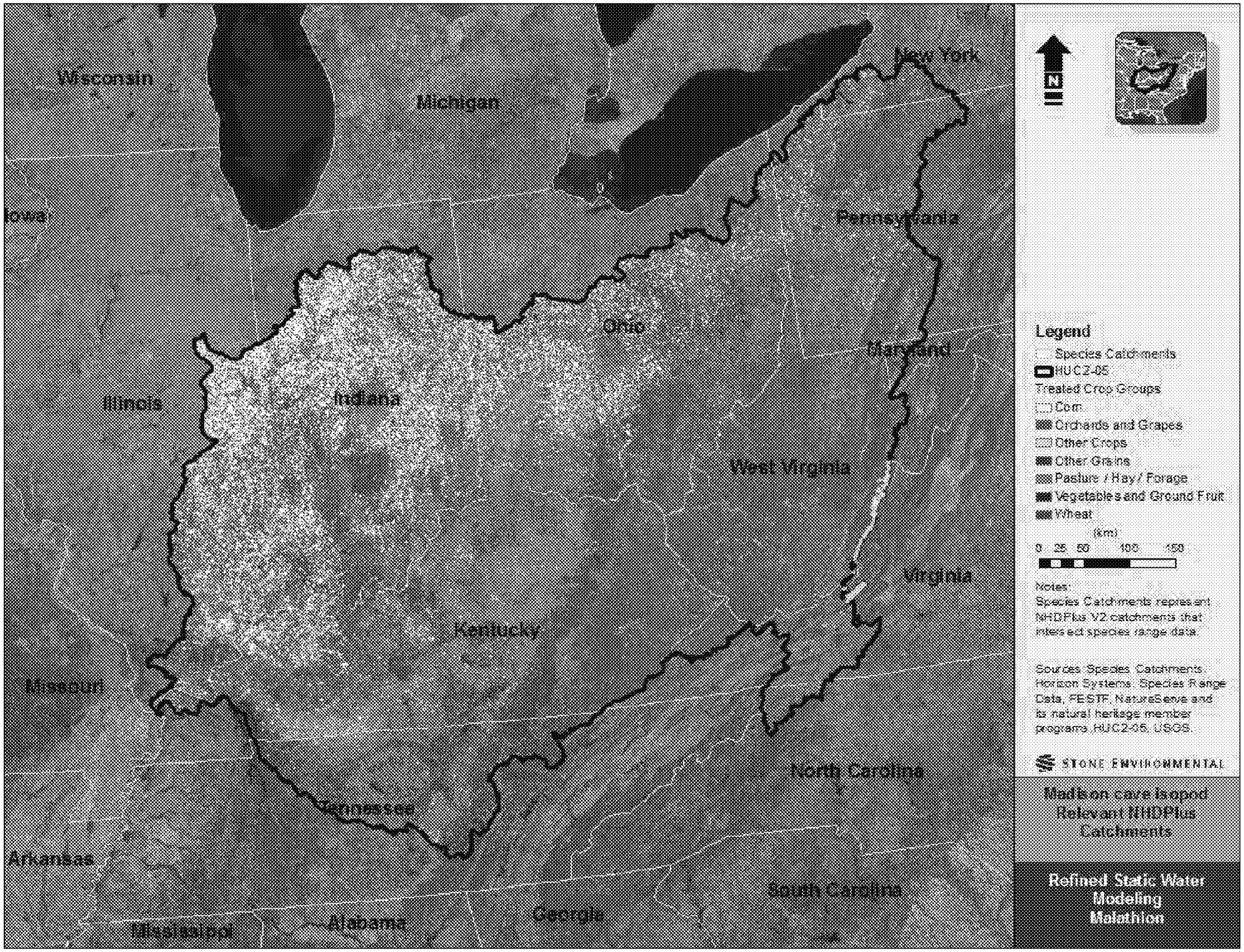


Figure 10. Madison cave isopod species catchment in HUC2 05.

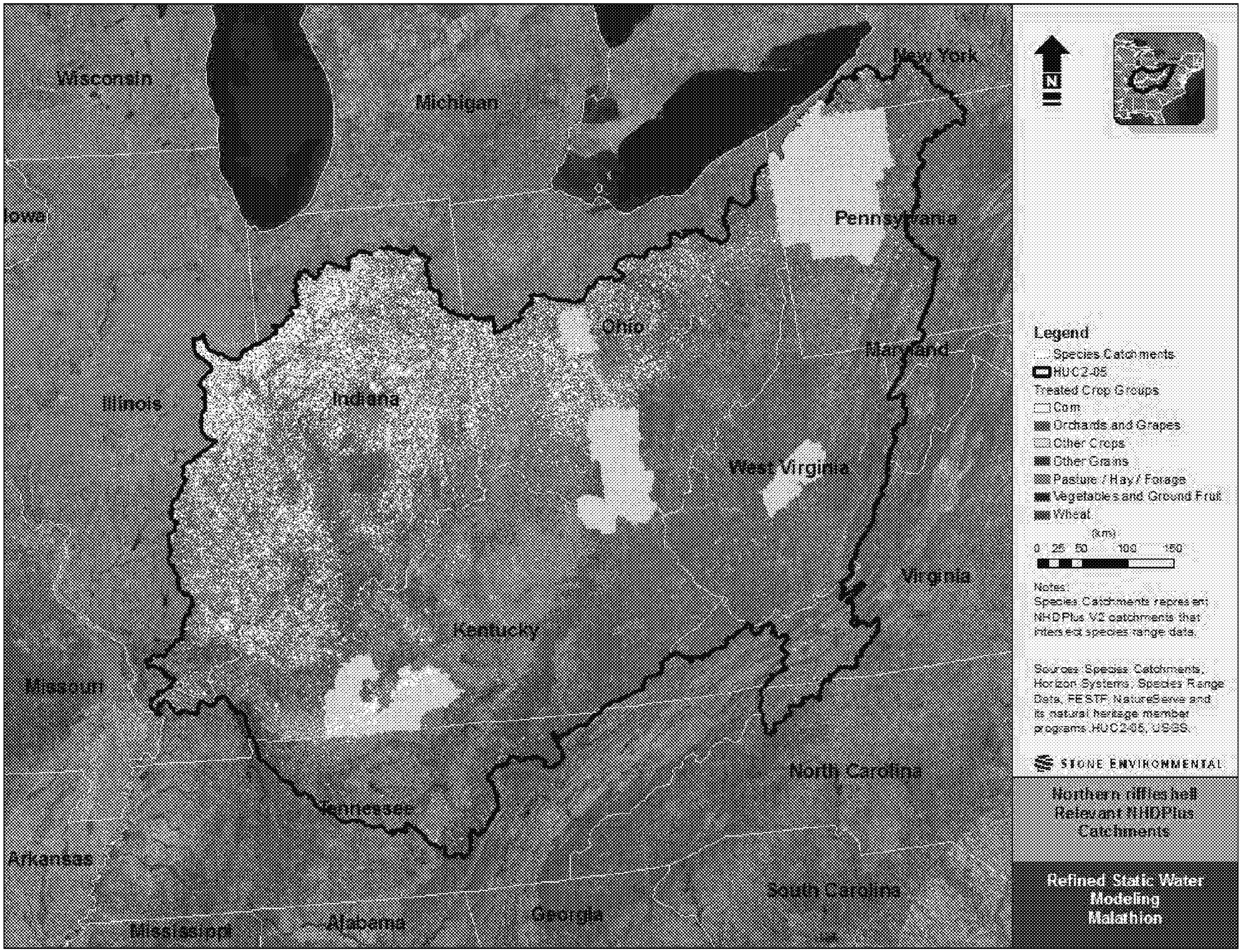
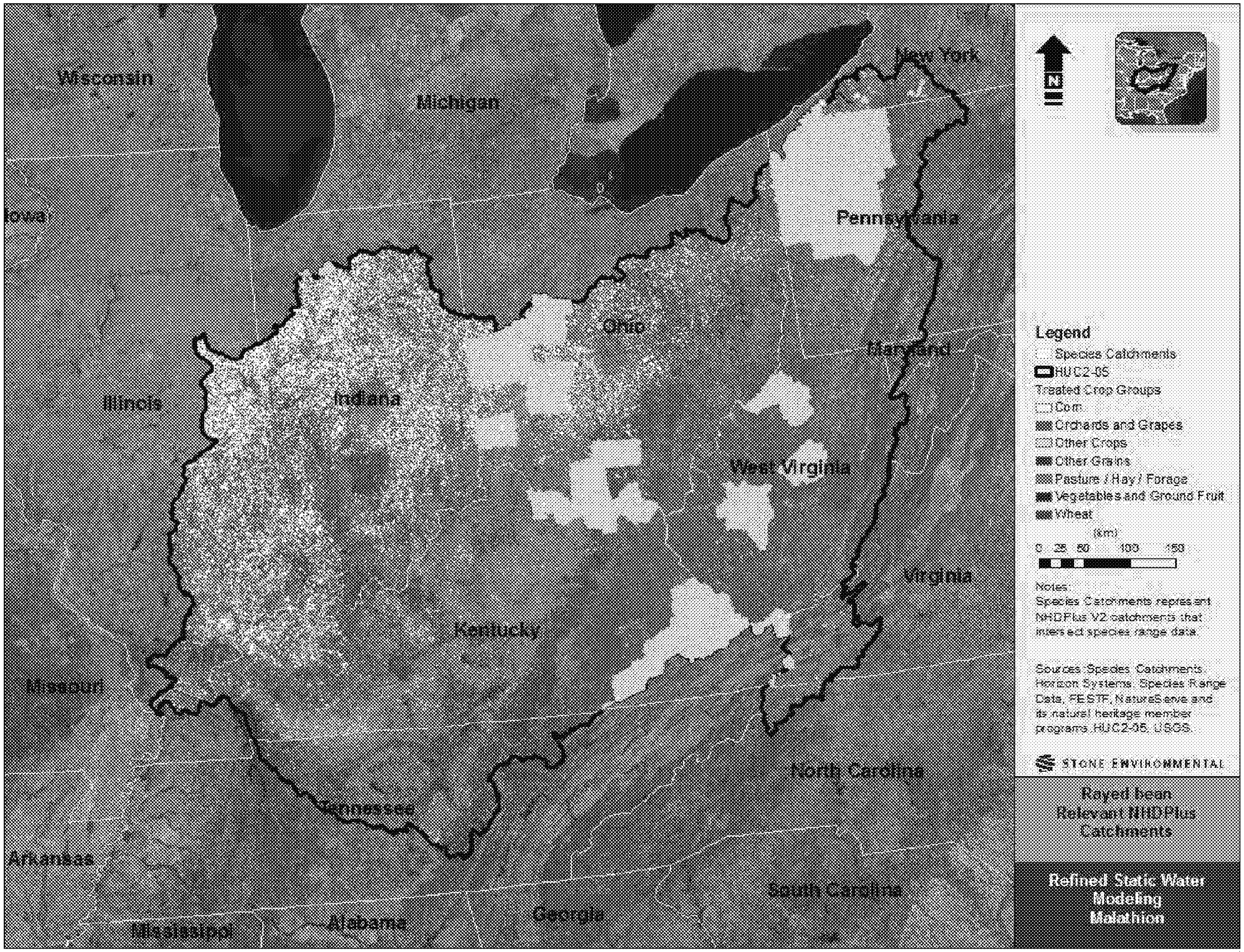


Figure 11. Northern riffleshell species catchments in HUC2 05.



Wisconsin
Michigan
New York
Iowa
Pennsylvania
Ohio
Maryland
Illinois
Indiana
West Virginia
Virginia
Kentucky
Missouri
North Carolina
Tennessee
Arkansas
South Carolina
Georgia
Alabama
Mississippi
N
Legend
Species Catchments
HUC2-05
Treated Crop Groups
Corn
Orchards and Grapes
Other Crops
Other Grains
Pasture / Hay / Forage
Vegetables and Ground Fruit
Wheat
(km)
0 25 50 100 150
Notes:
Species Catchments represent NHDPlus V2 catchments that intersect species range data.
Sources: Species Catchments, Horizon Systems. Species Range Data, FESTF, NatureServe and its natural heritage member programs. HUC2-05, USGS.
STONE ENVIRONMENTAL
Rayed bean
Relevant NHDPlus
Catchments
Refined Static Water
Modeling
Malathion

Figure 12. Rayed bean species catchments in HUC2 05.

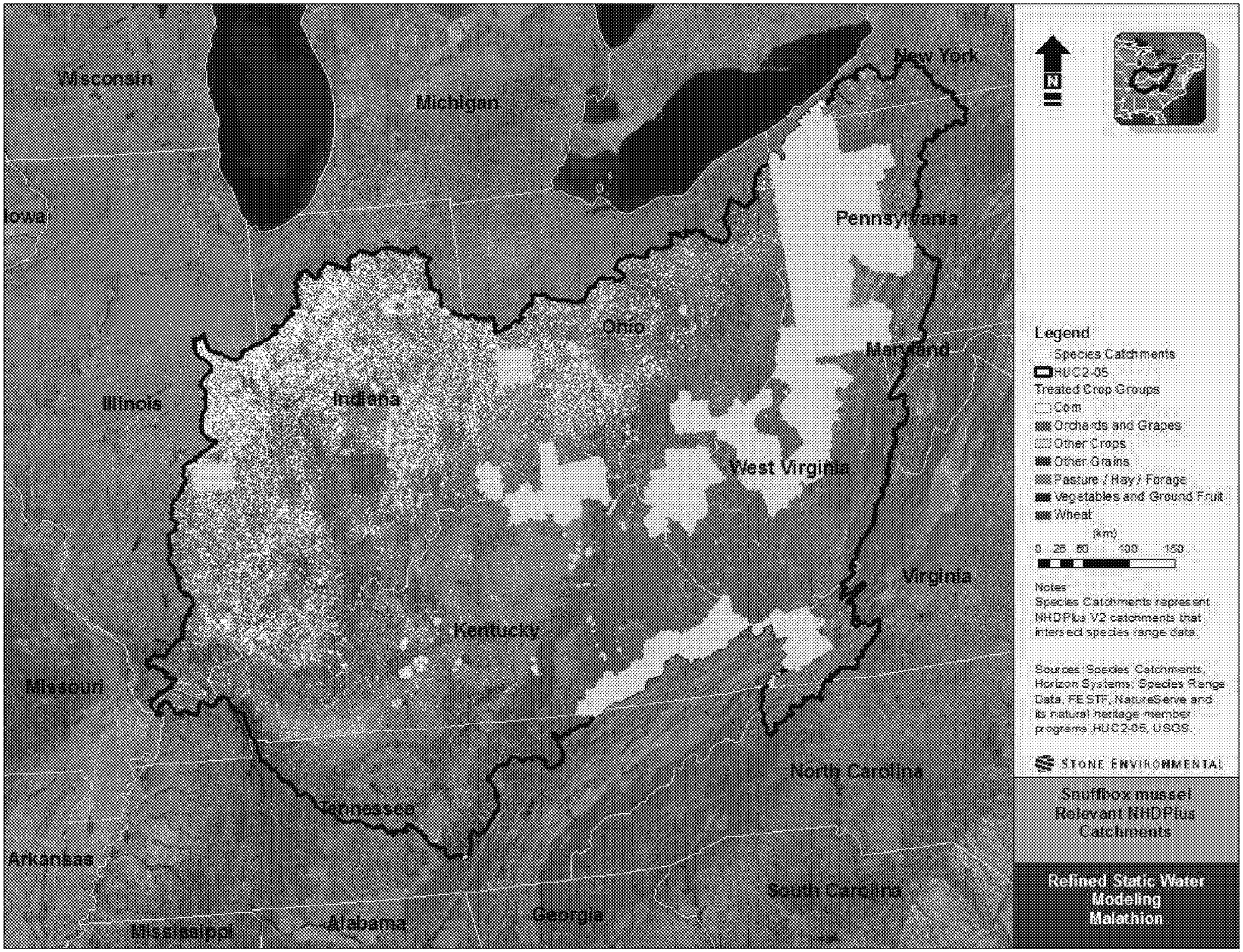


Figure 13. Snuffbox mussel species catchments in HUC2 05.

APPENDIX B APPLICATION WINDOW RESEARCH

In the Ohio River basin (HUC2 05) region, Alfalfa is primarily grown in Ohio, Indiana, and Kentucky (USDA OCE, 2012) where multiple cuttings are harvested from May-September (USDA NASS, 2010). Though MAL is rarely applied to alfalfa in Indiana (Christian Krupke, Professor of Entomology, Purdue University, personal communication, 4 May 2016; John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016), if used it would likely be to control alfalfa weevil larvae from early April to mid-June or potato leafhopper from mid-June to mid-September depending on stem sampling results and plant height (Purdue IPM, 2009b; McCormick et al., 2015; UK Extension, 2004). Based on this information and the long growing season with multiple harvest events for this crop, the MAL application window for alfalfa was estimated at 7 April-15 September.

Clover production is minimal in this region and it is unlikely that MAL or other insecticides are regularly applied to this crop in Indiana (John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016) or Ohio (McCormick et al., 2015). Clover is seeded from February-April (UK Extension, 1996) and may be plowed down in the spring (April-June) of the second year or cut every 35-42 days throughout the summer (SARE, 2007; UK Extension, 2013). If applied, MAL would be used to control alfalfa weevil larvae from early April to mid-May or adult potato leafhoppers from mid-June to mid-September (Purdue IPM, 2009b). Based on these references, the MAL application window for clover was estimated at the same date range as alfalfa (7 April-15 September).

Corn is a major crop in this region and is produced primarily in Indiana, Ohio, and Kentucky (USDA OCE, 2012) where it is typically planted from April-June and harvested from September through November (USDA NASS, 2010). MAL is minimally applied in Indiana (Christian Krupke, Professor of Entomology, Purdue University, personal communication, 4 May 2016; John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016), but can be applied to control corn leaf aphid and Japanese beetles in sweet corn (IPM Centers, 2001). However, given the many labeled pest insects that can attack corn (Cheminova, 2011; Cheminova, 2012; Purdue IPM, 2009a), MAL could potentially be applied at any point from 1 May-1 October depending on the pest problem. This was the application window chosen.

In this region, cotton is produced only in western Tennessee (USDA OCE, 2012) where it is planted from April-June and harvested from September-November (USDA NASS, 2010). Organophosphate insecticide use is discouraged during planting season, so most MAL applications would be likely to occur from 1 July-1 November before the final harvests (UT Extension, 2016). This was the application window selected for cotton.

Hops is a new and very minor crop in this region (John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016) and minimal insecticide use occurs at this point given the lack of specific control recommendations (UK Extension, 2012). If used at all, it may be applied to control aphids, spider mites, or Japanese beetles throughout the growing season in Ohio and Indiana (OSU Extension, 2014; Purdue Extension, 2015). Thus, the estimated application window was 1 May-1 September.

In this region, peaches are grown in Ohio, western Pennsylvania, Kentucky, Indiana, and Tennessee (USDA OCE, 2012) where harvest generally occurs from 1 June-15 September (ISDA, n.d.; UK Extension, 2007). Though rarely applied in Indiana or Pennsylvania (Rick Foster, Fruit & Vegetables Specialist, Purdue

Extension Entomology, personal communication, 4 May 2016; Greg Krawczyk, Extension Fruit Tree Entomologist, Pennsylvania State University, personal communication, 6 May 2016), MAL can be used to control spotted wing Drosophila and brown stinkbugs three weeks before harvest (Midwest Fruit Workers Group, 2016). As such, the estimated application window for peaches was 10 May-25 August based on this information and harvest dates.

Rye is grown mainly as a minor cover crop in Kentucky and Indiana and does not receive MAL treatment (John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016). MAL is recommended for armyworm control in May if scouting reveals major infestation (OSU Extension, 2013; OSU Extension, 2015). The application window was estimated at 1 April to 1 June.

In this region, strawberries are grown mainly in Ohio, but also in western Pennsylvania, Indiana, and Kentucky (USDA OCE, 2012). Planting typically occurs from 15 April-15 May and harvest occurs soon after beginning in June and continuing through August depending on the cultivar (OSU Extension, 2006). MAL is rarely applied in Indiana (Rick Foster, Fruit & Vegetables Specialist, Purdue Extension Entomology, personal communication, 4 May 2016) and not listed as a recommended control in the Midwest (Midwest Fruit Workers Group, 2016). The application window was estimated at 15 Apil-15 May, though it is unlikely that MAL is applied with any frequency.

Finally, winter wheat represents another minor cover crop in Ohio, Indiana, and Kentucky (USDA OCE, 2012), where it may be planted from late September through November and harvested from June-July (USDA NASS, 2010). Because it is a cover crop, MAL treatment is not usually required for wheat and is not applied in Indiana (John Obermeyer, IPM Specialist, Purdue Extension Entomology, personal communication, 4 May 2016), though unusual pest insect problems could be controlled pre-harvest (UK Extension, 2016). The application was estimated at 1 May-1 July.

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